A STUDY OF DISSEMINATION MECHANISMS AND GOVERNANCE MANAGEMENT OF HEALTH-RELATED MISINFORMATION ON SOCIAL MEDIA IN CHINA

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Declaration

This work has not previously been accepted in substance for any degree and is not being concurrently submitted in candidature for any degree.

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Date...............29 November 2024............

STATEMENT 1

This thesis is the result of my own investigations, except where otherwise stated. Where correction services have been used the extent and nature of the correction is clearly marked in a footnote(s). Other sources are acknowledged by footnotes giving explicit references. A bibliography is appended.

As English is not my first language, I have used translation and grammar assistance tools including DeepL and Grammarly to help me express my ideas accurately in English. These tools were employed solely to overcome language barriers and improve readability while maintaining the originality and academic integrity of the research.

Signed.................Yitong Liu.......................(Candidate)

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STATEMENT 2

I hereby give consent for my thesis, if accepted, to be available for deposit in the University's digital repository.

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Date...............29 November 2024............

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Abstract

The rise of social media has transformed health information dissemination whilst accelerating the spread of health-related misinformation, posing significant threats to public health and social well-being. This study employs an exploratory sequential mixed methods approach to investigate the dissemination mechanisms of health information on social media and proposes governance strategies to mitigate the negative impact of misinformation. The study begins with a grounded theory analysis of 12 in-depth interviews and social media comments to identify key factors influencing health information adoption. Based on this, a theoretical framework with seven latent variables is constructed: information quality, information source, information channel, perceived usefulness, health information adoption, level of knowledge and cognitive involvement. Eleven hypotheses are proposed involving direct, mediating, and moderating effects. Subsequently, a questionnaire survey of 500 social media users is conducted. Through Structural Equation Modelling and path analysis, results show that information quality, information source, and information channel influence the health information adoption through perceived usefulness, with information quality showing partial mediation, and information source and information channel showing full mediation. Level of knowledge moderates the relationship between information quality and information channel with perceived usefulness, whilst cognitive involvement moderates the relationship between perceived usefulness and health information adoption. This study refines the health information adoption model, providing a theoretical perspective on the dissemination mechanisms of health information on social media. The findings offer practical guidance for governance strategies, such as enhancing information quality and credibility, improving users' health literacy and critical thinking skills, optimising health information dissemination mechanisms, refining policies and regulations and strengthening multi-stakeholder collaboration. Whilst the study is limited to a specific cultural context, it contributes to digital health communication research, laying the foundation for future cross-cultural comparisons and long-term evaluation of governance strategies.

Keywords: social media, health information adoption, health misinformation, dissemination mechanisms, mixed methods

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Abbreviations

AMOS	Analysis of Moment Structure
AVE	Average Variance Extracted
CFA	Confirmatory Factor Analysis
CFI	Comparative Fit Index
CI	Cognitive Involvement
CR	Composite Reliability
EFA	Exploratory Factor Analysis
ELM	Elaboration Likelihood Model
HIA	Health Information Adoption
IAM	Information Adoption Model
IC	Information Channel
IFI	Incremental Fit Index
IQ	Information Quality
IS	Information Source
KMO	Kaiser-Meyer-Olkin
LK	Level of Knowledge
MLE	Maximum Likelihood Estimation
NFI	Normed Fit Index
PU	Perceived Usefulness
RMSEA	Root Mean Square Error of Approximation
SEM	Structure Equation Modelling
SPSS	Statistical Package for the Social Sciences
TAM	Technology Acceptance Model
TLI	Tucker-Lewis Index
WHO	World Health Organization

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Chapter 1 Introduction

In the digital age, social media has become the primary platform for disseminating health-related information. However, it has also facilitated the rapid spread of misinformation. This can lead to public misunderstanding and panic, and prompt individuals to adopt inappropriate health behaviours, thus posing a serious threat to public health and social stability. Facing this increasingly serious challenge, it has become urgent to conduct a thorough study of the mechanisms of the spread of health-related misinformation on social media and propose effective governance strategies.

1.1 Overview

As the opening of the entire thesis, this chapter provides the background and overall framework of the research, outlining the main content and logical thread. The chapter begins by introducing the importance of social media in health information dissemination and its challenges, especially the spread of health-related misinformation. It clarifies the research aim, objectives and questions, defines the research scope, and expounds upon the theoretical and practical significance of the study. In addition, this chapter outlines the research methods used and provides a brief introduction to the overall structure of the thesis. This chapter provides a clear roadmap for the entire study, ensuring consistency and direction throughout the research process.

1.2 Background and Context

Prevalence and Influence of Social Media

In recent years, the prevalence of social media has shown significant growth. According to the latest statistics from Statista, as of May 2024, global active social media users exceeded 5 billion and are expected to exceed 6 billion by 2028 (Dixon, 2024). This trend is even more pronounced in China. The China Internet Network Information Center (CNNIC) report shows that as of December 2023, China’s Internet user base reached 1.092 billion, with social media users accounting for 97.7% (CNNIC, 2024).

This massive user base has laid the foundation for rapid information dissemination whilst also bringing new challenges.

The widespread use of social media has not only changed the way information is obtained but also refined the roles of users. Users have transformed from passive information receivers to active content creators and disseminators (Kaplan and Haenlein, 2010). However, this transformation has also risen to several issues, such as information cocoons, echo chamber effects, and confirmation bias (Cinelli et al., 2021). Research indicates that social media algorithms tend to recommend information consistent with users' existing views, thereby reinforcing their existing cognitions (Bakshy et al., 2015). This phenomenon is particularly evident in health information dissemination, potentially leading to the rapid spread of misinformation (Wang et al., 2019).

Dissemination of Health Information on Social Media

Social media has become a primary channel for the public seeking health information. Research shows that about 70% of social media users search for and share health-related information on social media platforms (Zhao and Zhang, 2017). Social media has become a key platform for information dissemination, particularly during public health crises, such as the COVID-19 pandemic (Cinelli et al., 2020).

However, the quality of health information on social media varies greatly. A study published on the WHO website shows that 51% of vaccine-related posts were misleading, and 60% of pandemic-related posts were misleading (WHO, 2022). This phenomenon highlights the double-edged effect of social media on health information dissemination: it is both an effective tool for rapidly spreading accurate information and a potential breeding ground for the spread of misinformation (Zhao et al., 2020).

Impact of Health Misinformation and Governance Challenges

The rapid spread of health misinformation has become a significant global public health challenge. The World Health Organization has termed this phenomenon an ‘infodemic’, emphasising the widespread nature and harmfulness of misinformation dissemination (WHO, 2020a). Research indicates that false health information can not only affect individual health decisions but also undermine public trust and compliance with public health measures (Pian et al., 2021).

In light of these challenges, social media platforms have implemented several measures. For example, China’s Weibo platform has introduced a ‘Weibo Rumour Debunking’ to promptly clarify widespread prevalent misinformation (Pang et al., 2022). Similarly, WeChat released its official rumour-refuting account, ‘WeChat Tencent Myth-buster’, to fight against the widespread misinformation (ibid). However, the effectiveness of these measures has yet to be evaluated, and social media platforms still face challenges in balancing the free flow of information and controlling the spread of misinformation.

Social Media and Health Information Dissemination in the Chinese Context

In China, social media platforms such as WeChat, Douyin, and Weibo play a central role in health information dissemination (Zhu et al., 2020). These platforms are not only the main channels for the public to obtain health information but also essential media for the government and health institutions to release official information (Pang et al., 2022).

The uniqueness of China’s social media environment also brings unique challenges. Firstly, a large number of Chinese social media users and the rapid speed of information dissemination mean that health misinformation can affect a large population in a short time. For example, during the early stages of the COVID-19 pandemic, misinformation about certain foods or traditional Chinese medicines preventing the virus was widely spread on WeChat Moments, triggering panic buying behaviour among the public (Zhang et al., 2020). Secondly, the closed nature of Chinese social media platforms and their algorithmic recommendation mechanisms may exacerbate the information cocoon effect. Research shows that social media users tend to receive information consistent with their own views, which may lead to the solidification and reinforcement of false health information (Cinelli et al., 2021).

Importance of Health Information Adoption Research

To effectively address the spread of health misinformation on social media, it is crucial to understand the mechanisms through which users evaluate and adopt health information. Research on health information adoption provides a scientific foundation for developing governance strategies that can both promote accurate information and mitigate the harmful effects of misinformation. Understanding the factors that influence how social media users process, evaluate and ultimately adopt health-related information enables the development of targeted interventions that enhance information literacy, support critical evaluation, and promote responsible sharing behaviours (Vraga and Bode, 2020a). Moreover, insights into adoption mechanisms can inform platform design modifications that prioritise credible health sources and enhance the visibility of accurate information (Bode and Vraga, 2018). The significance of health information adoption research extends beyond individual behavioural outcomes to broader public health implications, as patterns of information adoption collectively shape societal health knowledge, risk perceptions, and preventive behaviours during both routine health situations and public health emergencies (Swire-Thompson and Lazer, 2020).

In this study, Health Information Adoption (HIA) is specifically defined as the process through which social media users receive, evaluate, accept and potentially act upon health-related information. This multifaceted construct encompasses four key dimensions: (1) information endorsement—recognising the value of health content and showing approval through social media mechanisms (e.g., likes, upvotes); (2) information dissemination—sharing health content with others in one's social network; (3) behavioural application—adjusting personal health behaviours based on the adopted information; and (4) health management implementation—integrating the information's suggestions into one's health decisions and practices. This comprehensive operational definition transcends mere information exposure to encompass both social engagement with content and practical application in health contexts, providing a clear conceptual framework for understanding how health information influences user behaviour in social media environments.

1.3 Statement of the Problem

The rapid development of social media has fundamentally changed the landscape of health information dissemination, transforming how information is accessed and spread (Lewandowsky et al., 2012). While social media has become an important platform for the dissemination of health information, it also provides fertile ground for the rapid spread of false health information, posing a significant threat to public health (Shu et al., 2017). This threat has been particularly evident during the COVID-19 pandemic, severely disrupting pandemic control efforts (Loomba et al., 2021).

More worryingly, study shows that false information spreads much faster on social media than accurate information and has a broader range of influence (Vosoughi et al., 2018). This phenomenon is particularly evident in health information, potentially leading to erroneous health concepts among the public and even dangerous self-treatment behaviours (Sharma et al., 2017). The rapid spread of false health information not only misleads the public, but it can also trigger social panic, lead to incorrect medical practices, and undermine public trust in public health interventions, thereby exacerbating health problems (Wang et al., 2019).

This phenomenon is no longer isolated but has become systematic and widespread. Studies have found that health-related misinformation on social media platforms is widespread, mainly focusing on key areas such as vaccine safety, disease prevention and treatment, which has led to a continued decline in public trust in science and medicine and further fuelled the spread of misinformation (Chou et al., 2018). During major global health events, the complex interactions between these influencing factors further exacerbate the ‘infodemic’ phenomenon, making addressing health misinformation even more severe (Tangcharoensathien et al., 2020).

Current research is insufficient to fully reveal these influencing factors and their interaction mechanisms, leading to difficulties in formulating and implementing effective governance strategies (Wang et al., 2019). The key to solving this problem lies in a deep understanding of the adoption mechanism of health-related information on social media. By identifying and analysing the factors that influence the adoption of health information, a scientific basis can be provided for formulating effective strategies and measures, thereby promoting the effective dissemination of health information, reducing the harm of misinformation, improving public health awareness, maintaining the stability of social media platforms, and ultimately improving overall social well-being.

1.4 Research Aim and Objectives

Research Aim

This study aims to comprehensively investigate the dissemination and adoption mechanisms of health-related information on Chinese social media, providing theoretical and practical guidance for addressing health-related misinformation challenges. By promoting the effective dissemination and adoption of accurate health information, this study aims to reduce the harmful effects of health misinformation on individuals and society, enhance public health awareness, and maintain social safety and stability.

Research Objectives

1. To explore factors influencing the adoption of health-related information on social media

Through qualitative research, identify and understand the various factors that influence users’ evaluation, selection, and adoption of health information on social media platforms, including users’ perceptions, discrimination, and behavioural tendencies, thereby laying the foundation for subsequent theoretical model construction and quantitative research.

2. To construct a theoretical framework of factors influencing the adoption of health-related information on social media

Based on qualitative research results, develop a theoretical model that demonstrates how various influencing factors interact and collectively impact users' adoption of health information. This model serves as a framework for explaining and predicting user behaviour, providing theoretical support for subsequent quantitative research.

3. To examine the perception pathways of social media users in the process of adopting health-related information

Through hypothesis development based on the theoretical framework and quantitative research validation, investigate how social media users perceive the influence of different factors on their behaviour and decision-making processes. Understanding these perception pathways provides deeper insights into user behaviour, facilitating the design of more targeted intervention measures.

4. To propose governance and strategies recommendations for the management of health-related misinformation on social media

Based on the results of the analysis of influencing factors and perception pathways, formulate specific strategies and recommendations for social media platforms, policymakers, and other relevant stakeholders. These recommendations aim to help them manage and govern health-related misinformation more effectively and mitigate the negative impact of misinformation on society.

These research objectives are interrelated and mutually supportive. Exploring influencing factors (Objective 1) and constructing a theoretical framework (Objective 2) lay the foundation for an in-depth understanding of user perception pathways

(Objective 3). These findings collectively support the formulation of targeted management strategies and recommendations (Objective 4).

1.5 Research Questions

This study focuses on the Chinese social media context, and all the following research questions are investigated within this specific cultural and social environment:

1. **Qualitative Research Question**: What are the key factors influencing the adoption of health-related information on social media?
This question explores and identifies various factors affecting users' adoption of health-related information in the social media environment, supporting the achievement of the first research objective.

2. **Quantitative Research Question**: How do the identified influencing factors specifically affect the adoption pathways of health-related information on social media?
Building on the qualitative research findings, this question quantitatively analyses how the identified factors interact and influence the adoption process of health-related information by social media users. It validates the theoretical model developed from the qualitative phase and supports the achievement of the second and third research objectives.

3. **Comprehensive Research Question**: How can the effective dissemination of accurate health information be enhanced while reducing the spread of misinformation on social media?
This question integrates the research findings and results from both qualitative and quantitative phases to formulate practical strategies and recommendations. It focuses on identifying best practices for promoting the dissemination of accurate health information and reducing the harmful effects of misinformation, supporting the achievement of the fourth research objective.

This study design employs an exploratory sequential mixed methods approach, integrating qualitative and quantitative methods to comprehensively examine factors influencing health-related information adoption on social media and formulate effective management strategies. Table 1.1 provides an overview of how these methodological phases align with the research objectives and questions, demonstrating the integration of different methods in achieving the research aim.

Research Objectives	Research Questions	Methods	Data Collection & Analysis
1. To explore factors influencing the adoption of health-related information on social media	Qualitative RQ: What are the key factors influencing the adoption of health-related information on social media?	Qualitative Study	- Semi-structured interviews (n=12) - Social media comments analysis - Grounded theory analysis
2. To construct a theoretical framework of factors influencing the adoption of health-related information on social media	Quantitative RQ: How do the identified influencing factors specifically affect the adoption pathways of health-related information on social media?	Model Development	- Literature review - Framework construction - Scale development - Pilot study (n=120)
3. To examine the perception pathways of social media users in the process of adopting health-related information		Quantitative Study	- Questionnaire survey (n=500) - SEM analysis - Path analysis
4. To propose governance and strategies recommendations for the management of health-related misinformation on social media	Comprehensive RQ: How can the effective dissemination of accurate health information be enhanced while reducing the spread of misinformation on social media?	Integration & Synthesis	- Integration of qualitative & quantitative findings - Strategy development - Recommendations formulation

Table 1.1: Alignment of Research Objectives, Questions and Methods

A research roadmap is also determined by outlining the research approach and combining research objectives and methods, as shown in Figure 1.1.

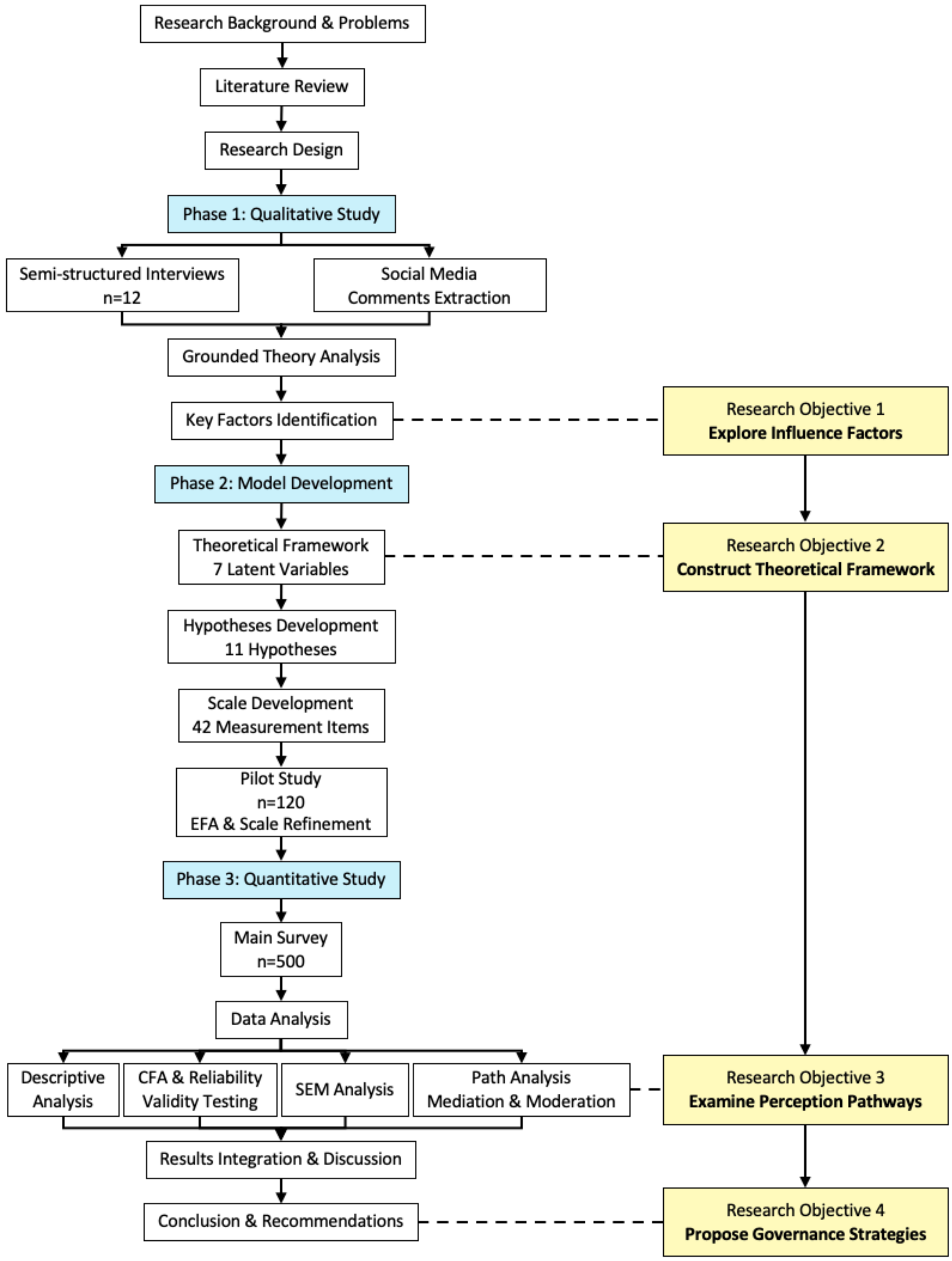

Figure 1.1: Research Roadmap

1.6 Scope of the Study

According to the research aim, this study design adopts a comprehensive and inclusive approach that consciously avoids over-segmenting the study population into specific demographically characterised groups. This approach is based on several key considerations.

Study Focus and Universality

This study focuses on the overall experiences and behaviours of all Chinese social media users, reflecting the universal accessibility of health information on these platforms. Health information adoption behaviour is viewed as a universal human need, not directly related to individual demographic characteristics. Regardless of age, gender, education level, or professional background knowledge, every social media user should be able to access high-quality, helpful information disseminated through reliable channels when seeking health information. This inclusive research approach ensures that the research results and recommendations can benefit a wide range of user groups, not just specific populations.

Methodological Considerations

From a methodological perspective, avoiding the over-segmentation of groups helps maintain a larger sample size, enhances statistical test power, and improves the generalisability and external validity of research results. Over-segmentation of groups would lead to smaller sample sizes, thereby weakening statistical test power and affecting the generalisability of research findings. This study aims to propose practical management strategies, but if the conclusions only apply to a few specific groups, the practical guiding significance would be significantly reduced. Additionally, social desirability bias is expected in the health field, and group differences may stem from expectations rather than actual behavioural differences. This study focuses on objective factors affecting actual behaviour, and fine-grained analysis might introduce irrelevant noise variables, affecting the interpretation of true causal relationships. The research can more accurately capture universal factors influencing health information adoption by avoiding over-segmentation.

Addressing Misinformation through Understanding Information Adoption

Whilst this thesis title focuses on health-related misinformation governance, the research strategically examines the broader mechanisms of health information adoption as the primary pathway to address the misinformation challenge. This approach stems from the recognition that misinformation cannot be effectively managed without first understanding how and why users adopt health information in social media environments. By identifying the factors that influence information adoption processes, this research provides the foundation for developing targeted strategies that can simultaneously promote the spread of accurate information and inhibit the adoption of misinformation.

This methodological approach offers several advantages over directly studying misinformation content. First, it avoids the need for medical expertise in distinguishing between accurate and inaccurate health claims, which lies beyond the scope of this research. Second, it acknowledges that the underlying psychological and social mechanisms of information adoption apply to both accurate and inaccurate content, making them crucial intervention points for governance. Third, this approach shifts focus from reactive correction to proactive shaping of information environments that naturally favour credible content.

Therefore, whilst the ultimate aim remains addressing health-related misinformation, the research deliberately focuses on health information adoption as the most effective conceptual framework for developing evidence-based governance recommendations. This strategic focus ensures that the research findings provide practical value for misinformation management without requiring content-specific medical evaluations.

Limitations and Applicability

Although the research focuses on social media users in China, it may be influenced by China's unique cultural, social, and regulatory factors. However, the basic principles and strategies derived from the research are expected to go beyond the Chinese context and provide guidance for international stakeholders. While this study focuses on identifying universal factors influencing health information adoption, it acknowledges that there might be refinements based on demographics that future research could explore. The universality of the research findings enables them to provide valuable references for managing health information on social media globally.

These ways align with the study's initial intention—all social media users can access accurate health information by avoiding over-segmentation of demographic characteristics. This study can better capture universal factors influencing health information adoption, providing insights and recommendations with broad applicability. It ultimately contributes to enhancing the effective dissemination of accurate health information globally.

1.7 Significance of the Study

This study provides insights and strategies for stakeholders to maximise the advantages of social media whilst minimising its potential harm. This study provides important theoretical and practical implications for the management of health-related misinformation on social media.

Theoretical Contributions

From a theoretical contribution perspective, this study constructs a comprehensive theoretical framework for explaining health information's dissemination and adoption in the social media environment. This theoretical contribution not only fills gaps in existing literature but also provides new theoretical perspectives and methodological guidance for future study. Based on the information adoption model and its derivatives, the study deeply explores the unique mechanisms and influencing factors of health information adoption in the social media environment. By integrating qualitative and quantitative research methods, this study not only verifies the applicability of existing theories in health information dissemination on social media but also expands the theoretical framework to include factors unique to social media. The findings of this research may provide reference or inspiration for future research directions, such as cross-cultural comparisons or longitudinal studies on the effectiveness of governance strategies. This theoretical innovation provides new ideas and methods for future research on health information dissemination on social media.

Practical Significance

In terms of practical significance, the research results directly translate into actionable strategies and recommendations, providing practical guidance for various stakeholders. These recommendations cover everything from improving individual users' information literacy to platform-level content management strategies and government-level policy formulation, providing comprehensive solutions for creating a healthier and more credible social media information environment. For ordinary social media users, this study provides ways for critically evaluating and adopting accurate health information, helping to improve their health information literacy and promote responsible information-sharing behaviour. For health organisations and professionals, the study results help them identify and implement effective communication strategies, making scientific knowledge more accessible and trustworthy to the public, thereby mitigating the negative impact of health misinformation. Social media platforms and news media can use the insights from this study to enhance self-regulatory mechanisms, creating a clearer and more reliable information environment. This not only benefits public health but also aligns with the long-term business interests of these platforms. For social and government managers, this study provides a scientific basis for formulating more effective public health policies and crisis communication strategies, helping to improve response capabilities in sudden public health events.

This study's significance lies in its comprehensive exploration of health-related misinformation issues on Chinese social media. By studying influencing factors and formulating effective strategies, the research provides actionable insights for various stakeholders, ultimately promoting a healthier, more information-transparent society. In the context of globalisation, although the research focuses on the Chinese social media environment, its findings and recommendations also have important reference value for understanding and addressing health information dissemination challenges on a global context.

1.8 Thesis Structure

This thesis comprises nine interconnected chapters that systematically address the research aim and objectives:

Chapter 1: Introduction

Establishes the foundation of the study by introducing the research background, problem statement, research aim and objectives, research questions, scope of investigation, and significance of the research.

Chapter 2: Literature Review

Critically examines existing literature on social media and health misinformation, providing a comprehensive analysis of definitions, classification frameworks, dissemination mechanisms, and current governance approaches. The chapter identifies significant research gaps and establishes the theoretical foundation through a detailed examination of information adoption models and their derivatives.

Chapter 3: Methodology

Articulates the philosophical underpinnings of the research, exploring ontological, epistemological, axiological, and methodological considerations. The chapter provides justification for adopting pragmatic mixed methods with a social constructivist stance, demonstrating alignment between research philosophy and the study's objectives.

Chapter 4: Methods

Outlines the operational aspects of the research design, detailing data collection strategies, sampling methods, instrument development, analysis techniques, and ethical considerations for both qualitative and quantitative phases. This chapter provides the methodological bridge between theoretical frameworks and empirical investigation.

Chapter 5: Qualitative Findings

Presents and analyses the results from the qualitative phase, including in-depth interviews and social media comment analysis. Through systematic application of grounded theory analytical processes, this chapter identifies key factors influencing health information adoption and establishes the groundwork for subsequent model development.

Chapter 6: Model Development and Hypotheses

Leverages qualitative findings and theoretical insights to develop a comprehensive research model with specific hypotheses addressing direct effects, mediation effects, and moderation effects. The chapter details measurement scale development, validation through pre-survey testing, and refinement processes that ensure construct validity.

Chapter 7: Quantitative Results

Reports the findings from the quantitative survey, presenting descriptive statistics, reliability and validity assessments, structural equation modelling outcomes, and path analyses that test the hypothesised relationships. The chapter provides systematic evaluation of both mediation and moderation effects within the theoretical model.

Chapter 8: Discussion

Synthesises qualitative and quantitative findings, critically evaluating results against existing literature and theoretical frameworks. The chapter addresses methodological considerations, acknowledges study limitations, and contextualises findings within the broader research landscape.

Chapter 9: Conclusion and Recommendations

Concludes the thesis by revisiting research objectives and questions, synthesising key findings, articulating theoretical contributions, and proposing practical governance strategies. The chapter outlines directions for future research and provides final reflections on the study's implications.

In summary, these chapters progressively build from existing knowledge (Chapter 2), through methodological justification and research design (Chapters 3-4) and empirical investigation (Chapters 5-7), to theoretical and practical contributions (Chapters 8-9). This structured approach ensures a comprehensive and coherent treatment of the research questions. This structural arrangement progresses logically from theoretical construction through empirical validation to practical guidance, with each chapter building upon previous findings to form a cohesive research cycle.

1.9 Chapter Summary

This chapter provides an overview of the study. Firstly, it emphasises the urgency of the research background, pointing out that the spread of health misinformation on social media has become a pressing issue. Secondly, it clarifies the research aim and objectives: explore influencing factors, construct a theoretical model, analyse influence pathways, and ultimately propose effective governance strategies. The research questions address one qualitative research question, one quantitative research question, and one comprehensive research question in line with the research objectives. The study scope covers Chinese social media users as a whole, not limited to specific demographic groups, whilst focusing on the dissemination and adoption of health information overall, including both health information and misinformation. This inclusive approach can provide insights and strategies with broad applicability. The chapter emphasises the dual significance of the research: theoretically refining the health information adoption model and practically providing a basis for formulating targeted governance strategies. In terms of research methodology, it elaborates on the rationale for adopting an exploratory sequential mixed methods approach, including in-depth interviews and social media comment analysis in the qualitative phase, theoretical framework design in the model construction phase, and questionnaire survey and data analysis in the quantitative phase, to comprehensively and deeply understand this complex issue. Finally, it outlines the systematic structure of the thesis, with each chapter having its specific function and contribution, collectively forming a complete and coherent research framework.

The following Chapter 2 provides a comprehensive review of relevant literature, discussing the achievements and shortcomings of existing research and providing theoretical support for the construction of the theoretical model in this study.

Chapter 2 Literature Review

2.1 Overview

This chapter first explains the definition of social media and categorises various types of health-related misinformation commonly found on social media platforms. It then analyses the mechanisms of health-related misinformation dissemination on social media and critically examines the current research status on the governance of health-related misinformation. It finally summarises the gaps in existing research, clarifying the theoretical basis for this study.

2.2 Definition of Social Media

Social media is an internet-based digital environment that facilitates the creation, sharing, and exchange of information, ideas, and content between individuals and communities (Carr and Hayes, 2015). Unlike traditional one-way communication models, social media platforms support two-way communication, enabling users to act as consumers and producers of content simultaneously (Kapoor et al., 2018). Social media includes various internet-based applications that provide channels for users to create, share, and interact with content in virtual communities and networks, such as social networking sites, blogs, wikis, and content-sharing sites (Kaplan and Haenlein, 2010).

One of the core features of social media is user-generated content (Roma and Aloini, 2019). Users can publish and share various forms of content in real time, including text, photos, videos, and audio, transforming from passive information consumers to active content contributors and curators (Kaplan and Haenlein, 2010). The technological foundation of social media is Web 2.0, which supports interactive, collaborative, and user-centric functionalities (Ngai et al., 2015). This evolution from static web pages to dynamic interactive platforms has significantly changed the way content is created and disseminated (Kapoor et al., 2018).

The diversity of social media platforms reflects their flexibility in meeting different user needs and communication purposes (Auxier and Anderson, 2021). As shown in Figure 2.1, the most widely used social media platforms include social networks (such as Facebook), video-sharing platforms (such as YouTube), photo-sharing sites (such as Instagram), and instant messaging applications (such as WhatsApp and Facebook Messenger). Although these platforms differ in functionality and user demographics, their common goal is facilitating communication and interaction between users (van Dijck and Poell, 2013).

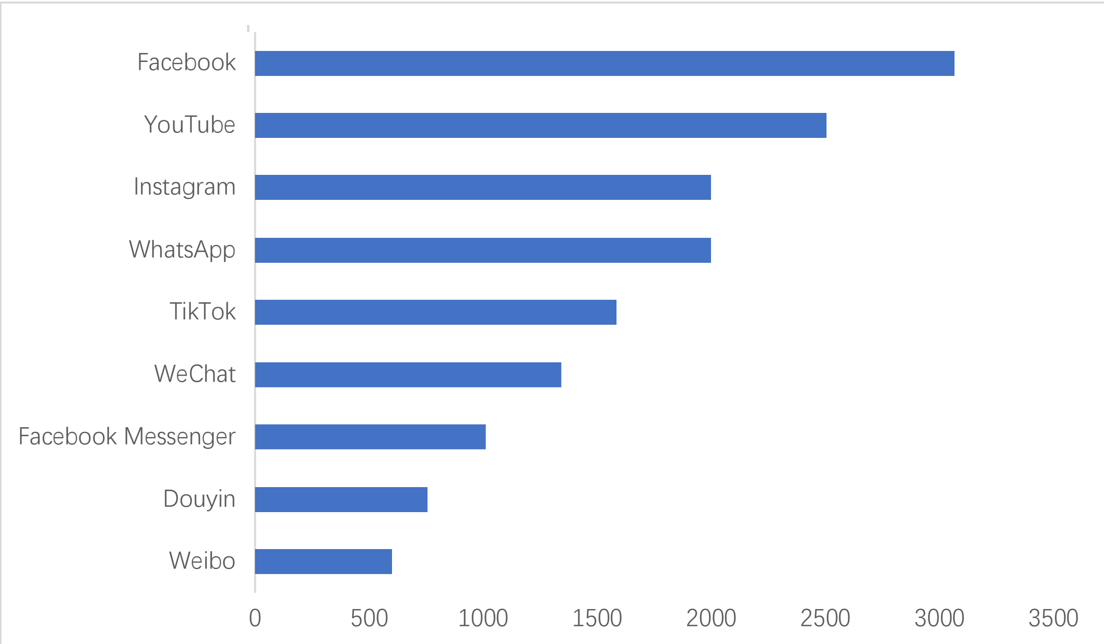

Figure 2.1: Most Popular Social Networks Worldwide as of April 2024 (in millions)

Social Media Platforms and Health Information Dissemination

Different social media platforms play unique roles in health information dissemination. To systematically understand their impact and characteristics, this study proposes a classification framework based on platform functionality, user interaction patterns, and information dissemination dynamics as shown in Table 2.1.

Platform Type	Key Features	Information Flow Dynamics	Examples	Health Information Impact
Open Social Networks	Public profiles, broad connections, algorithmic feeds	Wide, rapid spreading with less control; greater public visibility	Facebook, Weibo	High reach but lower trust; effective for official health communications
Closed Social Networks	Private groups, limited sharing, strong interpersonal ties	Slower, more contained spread, higher trust environment	WhatsApp, WeChat, Facebook Messenger	Higher trust but limited reach; stronger influence on health behaviours
Content-Centric Platforms	Media-rich sharing, limited text, less emphasis on identity	Visual content predominance with rapid viral potential	YouTube, Instagram, TikTok, Douyin	Effective for health education; emotional impact through visual content

Table 2.1: Framework for Classification of Social Media Platforms in Health Information Context

This classification framework provides a structured approach to understanding how different platform types of influence health information dissemination and adoption. Each category presents distinct opportunities and challenges for health communication and misinformation management. The discussion below examines specific major platforms as shown in Figure 2.1 through the lens of this framework, analysing how their unique characteristics shape health information flows:

Facebook: With 3.065 billion monthly active users (Statista, 2024), Facebook represents one of the most significant channels for health information dissemination. Health authorities increasingly utilise Facebook's features to disseminate health information and facilitate community engagement (Gesser-Edelsburg et al., 2018). However, research shows that while Facebook's health information dissemination is extensive, the accuracy and credibility of information still need improvement (Piedade et al., 2021).

YouTube: As a video-sharing platform with 2.504 billion monthly active users (Statista, 2024), YouTube has emerged as a crucial platform for health education and information sharing. Studies indicate that healthcare providers and medical institutions increasingly utilise YouTube for patient education and public health communication (Madathil et al., 2015). However, research also highlights concerns about the varying quality of health-related content on the platform (Li et al., 2020).

Instagram: With 2 billion monthly active users (Statista, 2024), Instagram's visual-centric approach offers unique opportunities for health communication. The platform's emphasis on images and short videos has proven particularly effective in reaching younger demographics with health messages (Lim et al., 2022).

WhatsApp and Facebook Messenger: These messaging platforms, with 2 billion and 1 billion monthly active users, respectively (Statista, 2024), facilitate more intimate and direct health communication. Research demonstrates their effectiveness in supporting healthcare delivery and health information sharing, particularly during public health emergencies (Manji et al., 2021).

WeChat: As China's dominant social platform with 1.343 billion monthly active users (Statista, 2024), WeChat integrates various functions that support health information dissemination, such as messaging, Moments, and official accounts (Pang et al., 2022). Studies show that its official accounts function plays a vital role in public health communication and health education in China (Sun et al., 2021).

Weibo: With 598 million monthly active users (Statista, 2024), Weibo also serves as a crucial platform for rapid health information dissemination in China. Research indicates its significant role in health risk communication and public health emergency response (Ren et al., 2023).

TikTok and Douyin: These short-video platforms, with 1.582 billion and 755 million monthly active users, respectively (Statista, 2024), represent emerging channels for health information dissemination. Their algorithmic content distribution and engaging format have shown particular effectiveness in reaching audiences with health messages (Basch et al., 2022).

The emergence of social media has fundamentally transformed how health information flows between healthcare authorities and the public. To understand this transformation, researchers have developed frameworks such as the Risk Amplification through Media Spread (RAMS) model (Vijaykumar et al., 2015). Drawing on the Social Amplification of Risk Framework (SARF) and the Socially Mediated Crisis Communication model (SMCC), the RAMS model explains how social media's unique characteristics influence the amplification and attenuation of risk information during public health events.

The application of such frameworks becomes particularly relevant when considering how different social media platforms shape health information dissemination through their distinct architectural features. The distinct characteristics of Chinese platforms like WeChat, Douyin and Weibo, compared to their Western counterparts, suggest that cultural factors significantly influence how health information flows through social networks. Studies have shown that platform-specific characteristics significantly influence information flow patterns. For example, WeChat's closed social circles and strong ties between users create more intimate but potentially echo chamber-prone information sharing environments (Pang et al., 2022), while Weibo's public networks facilitate broader but potentially more diffused information spread (Ren et al., 2023). Similarly, emerging platforms like Douyin present new dynamics through their algorithmic content distribution systems, which can rapidly amplify health-related content based on user engagement patterns rather than information accuracy (Liu et al., 2024). These platform-specific features introduce different opportunities and challenges for health information dissemination and governance. Therefore, understanding the characteristics of different social media platforms and their roles in health information dissemination is crucial for developing effective health information governance measures.

2.3 Classification of Health-related Misinformation

Health-related misinformation can be defined as health claims that lack scientific basis, contain inaccurate information, or present misleading content that potentially poses threats to public health through various mechanisms, including but not limited to treatment delays, increased disease transmission, and diminished trust in public health measures (Chou et al., 2018).

To systematically analyse the diverse forms of health misinformation circulating on social media, this study develops a comprehensive classification framework based on three dimensions: content domain, potential harm level, and information distortion mechanism as shown in Table 2.2.

Classification Dimension	Categories	Key Characteristics	Governance Implications
Content Domain	-Infectious diseases -Non-communicable diseases -Vaccines -Diet and nutrition -Drugs and smoking -Public health measures -Mental health	-Domain-specific knowledge required for verification -Different stakeholders involved	-Domain-specific expertise needed for correction -Targeted educational campaigns
Potential Harm Level	-Critical (immediate life threats) -Serious (significant health damage) -Moderate (potential health impacts) -Low (minimal direct health risk)	-Urgency of response -Scale of potential public health impact	-Prioritisation of governance resources -Response time requirements
Information Distortion Mechanism	-Fabrication (complete falsehood) -Manipulation (partially altered facts) -Miscontextualisation (facts in wrong context) -Oversimplification (complex information reduced)	-Different psychological impacts -Varying difficulty in detection	-Different correction approaches required -Specific literacy skills needed

Table 2.2: Framework for Classification of Health-Related Misinformation

This multi-dimensional framework provides a structured approach to understanding the complex nature of health-related misinformation circulating on social media. The intersections between these dimensions capture the multifaceted nature of real-world misinformation cases, where content domains, harm levels, and distortion mechanisms interact in various combinations. Based on this framework, this study examines specific categories of health-related misinformation from the content domain dimension, which has been most extensively documented in existing literature. Each category presents distinct characteristics, dissemination patterns, and governance challenges.

Infectious Disease-related Misinformation

Misinformation related to infectious diseases primarily involves inaccurate claims about disease transmission methods, preventive measures, and treatment options (Sell et al., 2020). During epidemics and pandemics, such as the West African Ebola outbreak in 2014-2016 (WHO, 2016a), the Zika virus epidemic in 2015-2016 (WHO, 2016b), and the COVID-19 pandemic from 2020 to 2023 (WHO, 2023a), the spread of such misinformation has been particularly prevalent and problematic. The COVID-19 pandemic has witnessed an unprecedented surge in health misinformation, which the World Health Organization termed an 'infodemic' (Zarocostas, 2020). This 'infodemic' is characterised by an overabundance of information, including false or misleading content, spreading rapidly through social media platforms and other outlets (Wang et al., 2021). The proliferation of COVID-19 misinformation has covered various aspects, including the virus's origin, transmission methods, prevention strategies, and treatment options, posing significant challenges to public health efforts and potentially undermining containment measures and vaccination campaigns (Rzymski et al., 2021).

Non-communicable Disease-related Misinformation

Misinformation about non-communicable diseases (NCDs) such as cancer, heart disease, and diabetes are another significant category. This type of misinformation often includes false claims about treatment methods, unscientific dietary advice, and exaggerated or false statements about drug efficacy (Islam et al., 2019). A study by Johnson et al. (2022) found that the most popular articles on social media about cancer contained misinformation, with many promoting herbs or supplements as cancer cures. These false claims often inaccurately portray unverified treatments as effective, contributing to widespread misinformation online. Similarly, cardiovascular disease-related misinformation often promotes 'miracle' foods or supplements claimed to prevent heart disease while downplaying the importance of lifestyle changes and medical interventions (Nagler, 2014). This is particularly concerning given the chronic nature of these conditions and the long-term adherence required for their management.

Vaccine-related Misinformation

Vaccine-related misinformation represents a significant threat to public health, often including false claims about vaccine safety, efficacy, and alleged side effects (Broniatowski et al., 2018). This type of misinformation is particularly prevalent on social media platforms and has substantially impacted public willingness to vaccinate. A prime example is the persistent false claim of a causal relationship between the measles, mumps, and rubella (MMR) vaccine and autism (Madsen et al., 2002). Despite being thoroughly debunked by numerous scientific studies, this misinformation continues to circulate on social media, leading to reduced vaccination rates and outbreaks of preventable diseases in various regions (Hussain et al., 2018). The COVID-19 pandemic has exacerbated the spread of vaccine misinformation (Carpiano et al., 2023). False claims about COVID-19 vaccines altering human DNA or containing microchips have proliferated online, significantly affecting vaccine acceptance rates (Nasiratu et al., 2023). A study by Loomba et al. (2021) found that exposure to vaccine misinformation reduced the intent to vaccinate by 6.2% in the UK and 6.4% in the USA among those who stated they would definitely accept a vaccine.

Diet and Nutrition-related Misinformation

Misinformation about diet and nutrition is widespread on social media platforms, often including unscientific weight loss methods, false claims about nutritional supplements, and inaccurate healthy eating advice (Denniss et al., 2023). These inaccuracies are frequently shared and amplified across various platforms, leading to the potential adoption of harmful dietary practices (ibid). Research has found that social media is rife with conflicting nutritional information. A study of UK consumers found that exposure to conflicting nutritional information through different media sources can lead to nutrition confusion and negative responses to health advice, potentially affecting healthy eating behaviours (Vijaykumar et al., 2021a). This constant exposure to contradictory information not only affects people's trust in nutritional advice on social media but also leads them to adopt unhealthy eating behaviours, which can have a negative impact on their overall health (Diekman et al., 2023).

Drug and Smoking-related Misinformation

Misinformation about drugs and smoking, including both prescription medications and recreational substances, poses significant risks to public health (Suarez-Lledo and Alvarez-Galvez, 2021). E-cigarette-related misinformation is a prominent example in this category. Despite growing evidence of potential health risks associated with e-cigarette use, social media content often portrays these products as completely harmless or significantly safer than conventional cigarettes (Kwon and Park, 2020). Misinformation about prescription drugs, particularly opioids, is another critical concern. Social media platforms have been used to spread false information about the safety and addictiveness of opioids, potentially contributing to the ongoing opioid crisis (ElSherief et al., 2024).

Public Health Measure-related Misinformation

Misinformation about public health measures becomes particularly prevalent during major health crises, such as the COVID-19 pandemic (Tasnim et al., 2020). This category includes false claims about the effectiveness of health interventions, misunderstandings of health policies, and incorrect information about using protective equipment (Swire-Thompson and Lazer, 2020). During the COVID-19 pandemic, social media platforms saw a surge in misinformation about mask effectiveness and social distancing measures, often undermining public compliance with these crucial interventions (Hornik et al., 2021).

Mental Health-related Misinformation

Mental health is another area significantly affected by online misinformation (Gao et al., 2020). This category includes stigmatising portrayals of mental health conditions, promotion of unscientific treatment methods, and dissemination of false mental health statistics (Robinson et al., 2019). Social media platforms often host content that perpetuates myths about mental health conditions, such as the notion that depression is merely 'feeling sad' or that anxiety disorders result from personal weakness (ibid). Moreover, unproven or potentially harmful mental health interventions are frequently promoted on social media, potentially leading individuals to forgo evidence-based treatments (Naslund et al., 2020).

While existing research has identified and categorised various types of health-related misinformation, it is important to note that these categories often overlap and interact in complex ways. For instance, vaccine misinformation may intersect with infectious disease misinformation during pandemics, while dietary misinformation might relate to both NCDs and mental health issues. Furthermore, the rapid evolution of social media platforms and communication patterns means that new forms and combinations of health misinformation continue to emerge. Therefore, understanding these interconnections and dynamics between different categories of health misinformation is important for developing effective health information governance measures.

2.4 Dissemination of Health-Related Misinformation on Social Media

Whilst social media platforms facilitate information exchange, they have also become channels for the rapid spread of false information (Wang et al., 2019). Within the context of globalisation, the dissemination of health-related misinformation on social media platforms has emerged as a significant focus of academic investigation, with research covering multiple platforms such as Twitter, Facebook, and Sina Weibo (Suarez-Lledo and Alvarez-Galvez, 2021). According to a report by the Council of Europe (Wardle and Derakhshan, 2017), research and policymaking on information disorder can be approached from three dimensions. Adapted to this study can be categorised as the information itself, the information disseminators, and the information recipients. These three elements interact to form a complex ecosystem that collectively influences the dissemination dynamics of health-related misinformation.

The Information

The content characteristics of health-related misinformation are key factors in its continued dissemination (Wang et al., 2019). These characteristics not only affect the speed and scope of information spread but also determine the attractiveness and persuasiveness of the information to the audience (Chou et al., 2018).

Health-related misinformation often appears with claims of authority and scientific evidence, frequently accompanied by images or videos to enhance credibility (Waszak et al., 2018). Research has shown that 40% of health-related posts on social media contain references to seemingly authoritative sources that are either non-existent or misrepresented (ibid). This strategy of disguising authority exploits public trust in professional knowledge, making it difficult for ordinary audiences to discern the authenticity of the information (Swire-Thompson and Lazer, 2020).

False health information typically employs specific content strategies, including visual presentation with text and images, use of specific numbers, and incorporation of trending topics (Sharma et al., 2017). Research has found that health-related posts with multimedia content receive more engagement than text-only posts (Zhang et al., 2019). These carefully designed content strategies enhance the attractiveness and persuasiveness of the information, making it more likely to be shared than purely scientific facts (ibid).

Content that targets specific cultural groups demonstrates a particular influence in spreading health misinformation. For example, a study in India found that diabetes videos targeted to South Asians were more misleading than those that were not culturally specific (Leong et al., 2018). This suggests that creators of misinformation may target content for specific groups, exploiting cultural differences and health concerns of particular groups to increase the appeal and credibility of the information. This strategy not only enhances the dissemination effect of the information but may also deepen health misconceptions within specific groups, causing more severe public health problems.

The simplification and misinterpretation of complex health information represent another significant characteristic (Swire-Thompson and Lazer, 2020). Scientific information on health is complex, and the dissemination of scientific information needs to be simplified for effective communication to the layperson (ibid). Information may be inadvertently oversimplified, distorted or exaggerated so that any oversimplification may lead to misinterpretation (Rigby and Naidu, 2023).

Emotional content plays a crucial role in the spread of health-related misinformation. Content that evokes strong emotions, particularly fear and anger, spreads significantly faster than neutral content (Vosoughi et al., 2018). This emotional manipulation not only increases the dissemination rate of information but may also affect the audience's judgment, making them more likely to accept unverified health claims (ibid).

The Information Disseminator

In the social media environment, the role and characteristics of information disseminators play a crucial role in the spread of health-related misinformation (Clemente-Suárez et al., 2022). Disseminators of misinformation can be categorised as 'well-intentioned disseminators' who believe the misinformation to be true and 'malicious disseminators' who know the misinformation to be false (Beauvais, 2022). These distinct types of disseminators demonstrate varying motivations and behavioural patterns, significantly impacting how health misinformation spreads and persists within social media ecosystems.

Well-intentioned disseminators are primarily individuals unaffiliated with official institutions, including so-called 'experienced patients'. These people may unintentionally become disseminators of false health information (Seymour et al., 2015; Chua and Banerjee, 2017). They usually share information out of goodwill, hoping to help others, but lack the professional knowledge to discern the authenticity of the information. This phenomenon reflects an important feature of the social media era, ordinary users have transformed from mere information recipients to major producers and disseminators of information. This role shift brings new challenges, such as how to improve public health information literacy whilst protecting freedom of speech.

In contrast, well-intentioned disseminators are malicious disseminators. This type of disseminator is mainly driven by profit but may also have motivations such as seeking attention, inciting social hatred, or pure entertainment (Wang et al., 2019). Professional fake news creators may use false health information to gain economic benefits such as advertising revenue or product sales. Some may spread misinformation for political purposes, attempting to influence public opinion or undermine social trust (ibid). The existence of this type of disseminator poses a severe challenge to social media platforms and regulatory bodies, requiring the development of more intelligent and effective identification and handling mechanisms.

The dissemination dynamics of health misinformation are not only influenced by the characteristics and motivations of individual disseminators but also shaped by the architectural features of social media platforms. For example, the closed social circles and Moments sharing function of WeChat may limit the scope of information diffusion compared to open platforms like Weibo (Pang et al., 2022), while the algorithmic recommendation mechanisms of Douyin may amplify the spread of eye-catching yet unverified health content (Liu et al., 2024). Therefore, understanding how platform-specific affordances interact with disseminator behaviours is crucial for developing targeted governance strategies.

The psychological characteristics of disseminators significantly influence sharing behaviour. Studies have shown that content evoking high-arousal emotions is more likely to be shared on social media (Vosoughi et al., 2018). This tendency reflects fundamental human social and emotional needs in information-sharing behaviour (Brady et al., 2017). This explains why emotionalised health information, whether true or false, is often more easily spread than neutral scientific facts.

Risk perception significantly influences information-sharing behaviour during health crises. Studies have shown that heightened risk perception during public health emergencies can lead to increased information sharing without adequate verification (Oh et al., 2021). This increased sharing behaviour during crisis periods may be attributed to emotional responses and survival-oriented decision-making (Lwin et al., 2018).

The Information Recipient

The characteristics of information recipients significantly affect their ability to identify and process health-related misinformation. These characteristics include demographic features, cognitive abilities, and personal experiences and preferences (Guess et al., 2020).

Demographic characteristics play an important role in identifying health-related misinformation susceptibility, though findings across studies show subtle age-related patterns. While Brashier and Schacter (2020) found that older adults may face challenges in discerning false health information in certain contexts, another research reveals a more complex picture. A randomised survey experiment among WhatsApp users in the UK and Brazil by Vijaykumar et al. (2021b) found that younger adults demonstrated stronger misinformation beliefs than older adults regarding COVID-19 misinformation. Their study also identified potential backfire effects of corrective information among older adults in the UK, suggesting age-specific responses to both misinformation and correction attempts. These varied findings may reflect complex interactions between age, digital literacy, and information environments. Guess et al. (2019) suggest that different age groups access information through different channels—younger people may rely more heavily on social media while having less exposure to traditional authoritative sources, whereas older adults may have different digital platform experiences and fact-checking approaches. These findings collectively emphasise the importance of developing differentiated, age-appropriate health education and misinformation interventions tailored to specific population segments.

Cognitive beliefs are also crucial factors influencing information reception. Individuals with more vital analytical thinking skills typically process information more critically, while those with more intuitive thinking styles are more susceptible to believing false health information online (Pennycook and Rand, 2019). This suggests that cultivating critical thinking and information literacy is crucial for resisting misinformation. Educational systems and public health institutions should emphasise cultivating these abilities as a long-term strategy for addressing health-related misinformation (Vraga and Bode, 2021).

Selective exposure and confirmation bias play essential roles in information processing. People tend to seek information supporting their existing views and avoid information contradicting their beliefs (Meppelink et al., 2019). This tendency is more pronounced in the internet environment, leading to the fragmentation of information domains and the formation of online echo chambers (Cinelli et al., 2021). Social media algorithms typically recommend content based on users' interests and behaviours, further reinforcing this effect and making it easier for users to fall into information cocoons (Geschke et al., 2019). This phenomenon poses a severe challenge to public health communication, and how to break these information cocoons and ensure correct health information reaches all populations has become an urgent problem to be solved.

Additionally, factors such as digital literacy, health literacy, subjective judgment, cultural background, and emotions also affect how information recipients process information. For example, individuals with higher health literacy demonstrate a better ability to evaluate health information quality and are less likely to share misinformation (Keselman et al., 2021). Cultural background may influence people's understanding and acceptance of certain health concepts (Brooks et al., 2019). The complexity of these factors requires a multidimensional, interdisciplinary approach to studying and addressing the spread of health-related misinformation.

In conclusion, the dissemination of health-related misinformation represents a complex ecosystem involving multiple interacting elements: the characteristics of the information itself, the motivations and psychology of the disseminators, and the personal characteristics and cognitive tendencies of the recipients (Wang et al., 2019). While existing research has identified these key mechanisms individually, the interactions between these elements remain challenging to study comprehensively. Additionally, the rapid evolution of social media environments and the emergence of new platforms like Douyin create persistent challenges for understanding these dissemination dynamics. Platform-specific features—such as WeChat's closed social circles, Weibo's public networks, and Douyin's algorithmic recommendation mechanisms—significantly influence how health information flows through digital ecosystems. Understanding these complex interactions and platform-specific dynamics is crucial for developing effective strategies to combat health misinformation and inform the governance approaches that follow.

2.5 Current Research on the Governance of Health-Related Misinformation

The governance of health-related misinformation represents a complex, multi-stakeholder approach to managing the creation, dissemination, and impact of inaccurate health information. In this context, governance refers to the coordinated set of policies, technical systems, regulatory frameworks, and collaborative mechanisms aimed at detecting, preventing, and mitigating the spread and impact of false or misleading health information across digital platforms, with particular emphasis on social media environments.

Effective health misinformation governance encompasses several critical components that function as an integrated ecosystem rather than isolated interventions. Content moderation and removal mechanisms represent a fundamental aspect of platform-level governance. Gillespie (2018) examines how social media platforms implement policies and practices for identifying and removing false health content or reducing its visibility through downranking, labelling, or limiting sharing capabilities. During the COVID-19 pandemic, major platforms like Facebook and Twitter implemented specific content moderation policies for health misinformation, though with varying effectiveness and transparency (Papakyriakopoulos et al., 2020).

Algorithm design and technical approaches to content distribution constitute another crucial governance component that complements content moderation. Algorithmic systems not only detect problematic content but also influence its visibility and reach. Platforms employ various technical approaches to address health misinformation through their recommendation systems. Ozbay et al. (2020) examine how different algorithmic approaches can be used to detect and limit the spread of health misinformation across social media platforms. Empirical studies have demonstrated that algorithmic interventions can affect the spread of health misinformation; for instance, Sharevski et al. (2022) found that Twitter's soft moderation approach using misinformation warning labels had significant effects on users' belief in COVID-19 vaccine misinformation, though these effects varied based on users' prior beliefs and political orientation.

Cross-sectoral collaboration between technology companies, health organisations, government agencies, and civil society forms the third essential element of comprehensive governance. The World Health Organization (2020b) has emphasised the importance of such partnerships in addressing health misinformation, particularly during global health emergencies. Tangcharoensathien et al. (2020) document how the WHO Information Network for Epidemics collaborated with social media companies during the COVID-19 pandemic to rapidly disseminate accurate information and counter misinformation across multiple platforms. These collaborative governance approaches recognise that no single entity possesses all the necessary expertise and resources to address complex health misinformation challenges.

User education and literacy programs represent a preventive approach to governance that builds resilience at the population level. Vraga and Bode (2017) examine how improving public ability to critically evaluate health information can reduce susceptibility to misinformation, while Jones-Jang et al. (2021) demonstrate that different types of literacy—including health, media, and digital literacy—contribute uniquely to individuals' ability to identify false health information. Tully et al. (2020) tested news literacy messages aimed at mitigating the impact of health misinformation, finding that such messages can alter misinformation perceptions, but typically require multiple targeted messages rather than single interventions. These studies highlight that building public resilience to misinformation requires sustained and multifaceted literacy efforts rather than one-time interventions.

Regulatory and policy frameworks provide the structural foundations for platform accountability and establish the boundaries within which other governance mechanisms operate. Flew et al. (2019) examine the shifting dynamics between digital platforms and traditional media regulation, noting how content moderation has become a critical site for debates about platform governance and the balance between public interest obligations and free expression. Tenove (2020) analyses disinformation governance approaches, identifying normative challenges facing democratic societies, including the appropriate roles for state, corporate and civil society actors in managing problematic online content. These governance structures vary significantly across cultural and political contexts, reflecting different assumptions about the role of regulatory interventions in information ecosystems.

These five governance components—content moderation, algorithmic design, cross-sectoral collaboration, user education, and regulatory frameworks—function as an interconnected system rather than isolated interventions. The effectiveness of content moderation depends on appropriate regulatory frameworks and algorithmic support, while user education programs must align with platform affordances and cultural contexts. Wang et al. (2019) emphasised the need for interdisciplinary approaches to identify effective interventions, suggesting that multi-faceted strategies may be required to address this complex issue.

With this comprehensive governance framework in mind, current research primarily divides governance strategies into three temporal approaches based on intervention timing: beforehand warning, halfway identification and prevention, and afterwards correction (Vraga and Bode, 2020b). Each temporal approach leverages different components of the governance ecosystem and presents unique advantages and limitations.

Prebunking Interventions: Building Resilience Before Exposure

Prebunking interventions encompass preventive measures implemented prior to public exposure to misinformation. This approach derives its name from the concept of psychological inoculation, where exposure to weakened forms of misinformation can build cognitive resilience against subsequent stronger exposure (van der Linden et al., 2017). The core objective of prebunking is to enhance public information literacy and critical thinking skills, thereby mitigating the impact of health misinformation before it reaches its audience.

Research consistently demonstrates that prebunking strategies can effectively weaken the influence of misinformation. Pennycook et al. (2020) found that simple accuracy nudges before exposure to misinformation significantly reduced the likelihood of believing and sharing false health claims. This effectiveness stems from altering people's default trust attitude toward information, increasing analytical thinking and healthy scepticism when encountering health-related content (Pennycook et al., 2021).

Prebunking manifests in several complementary approaches within social media environments. The implementation of warning labels represents one of the most direct platform-level interventions. Clayton et al. (2020) demonstrated that adding warning labels about potential misinformation on social media platforms effectively reduced the spread of health-related rumours. These visual cues serve as cognitive triggers that activate critical evaluation before users engage with or share content. The timing of these interventions proves crucial, as Brashier et al. (2021) found that prebunking warnings are more effective than afterwards corrections, reducing misinformation sharing by up to 25.3% when implemented before exposure. This significant reduction occurs because prebunking prompts people to adopt a more cautious and analytical stance when receiving information.

Beyond platform features, broader educational initiatives form another essential component of prebunking strategies. Merchant and Lurie (2020) emphasise the importance of science popularisation education in increasing public acceptance of scientific knowledge and resilience against health misinformation. These educational approaches focus on developing transferable skills that help users evaluate health information across different contexts and platforms. Similarly, Vraga and Bode (2021) argue that media literacy interventions provide users with the tools to identify common misinformation techniques and critically assess health claims they encounter online.

Technological approaches to prebunking continue to evolve as social media platforms develop. Neubeck et al. (2015) explored the potential of using mobile technologies for preventive health interventions, suggesting technological pathways for delivering prebunking content. More recently, interactive approaches like educational games have shown promise in building resistance to misinformation by allowing users to experience the creation of misinformation in controlled environments (Roozenbeek and van der Linden, 2019).

Despite its demonstrated effectiveness, prebunking approaches face several implementation challenges. These include the need for ongoing reinforcement of literacy skills, difficulties in reaching diverse populations with varying knowledge levels, and the challenge of addressing novel misinformation tactics that constantly evolve in social media environments. Additionally, the effectiveness of prebunking may vary across different types of health misinformation and different cultural contexts (Swire-Thompson and Lazer, 2020).

These limitations highlight the need for comprehensive strategies that combine prebunking with other approaches to health misinformation governance. As Wang et al. (2019) note, misinformation is easy to spread but difficult to govern, suggesting that no single approach will prove sufficient. Prebunking represents a crucial first line of defence, ideally complemented by timely identification and correction mechanisms within a comprehensive governance framework.

In-process Detection and Intervention: Managing Active Misinformation

In-process detection and intervention strategies target health misinformation during its active circulation phase on social media platforms. This approach acknowledges a fundamental challenge in misinformation management: once false health information begins spreading, containing its influence becomes increasingly difficult. Sharma et al. (2019) highlight this tension, noting that while in-process methods can reduce misinformation impact, complete elimination remains elusive. This difficulty stems partly from cognitive biases that affect information processing; as Pennycook et al. (2018) demonstrate, even when later corrected, repeated exposure to false claims tends to increase their perceived truth among audiences.

The evolution of technological detection approaches has progressed through several distinct developmental phases, each addressing different aspects of the misinformation challenge. Initial detection systems relied primarily on content-based analysis, examining linguistic patterns and factual inconsistencies. These approaches have now matured into sophisticated artificial intelligence frameworks. Kaliyar et al. (2021) exemplify this advancement through their bidirectional training-based deep learning approach, which achieved a remarkable 98.9% accuracy rate in fake news detection under controlled conditions. Such high-performance systems suggest the potential for automated, scalable solutions to the volume challenge of social media misinformation.

Theory-informed detection models represent a significant refinement in this technological evolution. Rather than treating detection as a purely technical problem, these approaches integrate established communication and persuasion theories to create more subtle systems. Zhao et al. (2021) demonstrate this integration through their health misinformation detection model based on the Elaboration Likelihood Model (ELM). By classifying health misinformation features into central-level (content quality) and peripheral-level (presentation and source) categories, their model achieves approximately 85% detection accuracy. This theory-guided approach offers deeper insight into why certain health misinformation spreads effectively and how detection systems can target those specific mechanisms.

As detection systems evolved, researchers recognised that content analysis alone proves insufficient; misinformation spread patterns and network dynamics play equally crucial roles. This realisation led to the development of network-based intervention approaches. Shao et al. (2018) pioneered this direction by developing models that identify rumour sources and curtail automated spreading mechanisms like social bots. By targeting dissemination vectors rather than just content, these approaches address the structural dimensions that facilitate rapid misinformation spread across platforms.

The urgency driving these technological developments becomes clear when examining the viral mechanics of misinformation. Vosoughi et al.'s (2018) landmark study of 126,000 Twitter stories revealed that false news consistently reached more people than truthful content, with the top 1% of false news cascades routinely diffusing to between 1,000 and 100,000 people. More concerning still, their research demonstrated that false information spreads farther, faster, and broader than accurate information. These dynamics create narrow intervention windows, emphasising why developing increasingly responsive detection systems remains a research priority.

Despite significant advances, in-process detection and intervention approaches face substantial challenges that limit their effectiveness. The inherent trade-off between speed and accuracy creates a persistent tension, as platforms must balance rapid response against the risk of incorrectly flagging legitimate health information.

Contextual nuances in health communication further complicate automated assessment, particularly across languages and cultural contexts. Additionally, as misinformation tactics continuously evolve in response to detection systems, platforms face an ongoing technological arms race that requires constant refinement and adaptation.

These limitations underscore why in-process detection, while essential, represents just one component in comprehensive governance frameworks. Effective management of health misinformation requires coordinated strategies spanning the entire information lifecycle, connecting prebunking initiatives with detection systems and correction mechanisms in integrated approaches tailored to platform-specific dynamics and evolving information environments.

Debunking Interventions: Correcting Established Misinformation

Debunking interventions focus on correcting health misinformation after it has been disseminated across social media platforms. Although this approach faces inherent time delays, it remains an essential component in comprehensive governance strategies. Chan et al. (2017) emphasise that effective correction should include both clarification of misinformation and reasonable causal explanations to mitigate its lingering impact. This dual approach addresses not only what information is incorrect but also why the misinformation initially appeared plausible, helping audiences replace false narratives with accurate understanding.

The design principles for effective debunking have evolved significantly through research. Lewandowsky et al. (2020) suggest that ideal corrective information should explain why the misinformation was initially believed to be correct and propose comprehensive alternative explanations. This approach recognises that simply labelling information as false without providing a coherent alternative often proves ineffective. By offering audiences a complete explanatory framework, debunking interventions can help displace the cognitive presence of misinformation with accurate understanding.

Implementation of debunking interventions on social media platforms takes several forms, each leveraging different platform affordances and correction mechanisms. Bode and Vraga (2018) explored how Facebook's algorithmic and social corrections could effectively address health misinformation about the Zika virus. Their research demonstrated that algorithmically selected corrections significantly reduced misperceptions, highlighting the potential for automated correction systems to scale debunking efforts across large user populations. Similarly, exposure to carefully designed visual corrections from authoritative sources can effectively counter misinformation. A study from the Centers for Disease Control and Prevention (CDC) showed that WHO-designed and shared infographics on social media could effectively prevent COVID-19 misinformation spread (Vraga and Bode, 2021).

The effectiveness of debunking varies considerably based on audience characteristics and message design factors. Demographic variables significantly influence correction receptivity. Brashier and Schacter (2020) found that older adults may be more susceptible to confusing true and false information even after corrections, suggesting the need for age-appropriate debunking strategies. Similarly, the relationship between correction content and audience worldviews plays a crucial role in effectiveness. Hornsey (2020) highlights that information consistent with the audience's existing beliefs is more likely to be accepted, while corrections that challenge fundamental worldviews often face resistance.

Message framing represents another critical factor in debunking effectiveness. Dickerson et al. (2021) found that correction messages using empathetic language were significantly more effective than those employing purely technical explanations. This finding underscores the importance of considering not just what information is presented in corrections, but how that information is framed and delivered. Empathetic framing may help overcome defensive reactions that often accompany direct challenges to previously accepted information.

These design considerations highlight the complexity of creating effective debunking interventions in diverse information environments. While research demonstrates that well-crafted corrections can substantially reduce belief in misinformation, complete elimination of misinformation effects remains challenging. It suggests that preventing exposure to misinformation through prebunking and limiting spread through in-process interventions should be prioritised whenever possible.

Despite these challenges, debunking interventions represent an essential component in comprehensive health misinformation governance frameworks. By integrating evidence-based debunking principles with prebunking strategies and in-process detection systems, platforms and health authorities can develop more effective responses to the complex challenge of health misinformation on social media. This integrated approach recognises that no single intervention type will prove sufficient given the diverse nature of health misinformation and the complex information ecosystems in which it spreads.

Connecting Research to Governance

The complex landscape of health misinformation governance reveals important connections to the current study's objectives. By exploring the mechanisms of health information adoption on social media, this research addresses a fundamental prerequisite for effective governance: understanding how and why users accept certain health information whilst rejecting other information. The factors that influence health information adoption—including information quality, source characteristics, and platform dynamics—directly inform which governance strategies might prove most effective in specific contexts. For instance, if users primarily adopt health information based on peripheral cues like source credibility rather than content quality, governance approaches emphasising authoritative sources might prove more effective than those focusing solely on content correction. Similarly, understanding how user characteristics like knowledge level and cognitive involvement moderate information adoption can help tailor prebunking and debunking interventions to specific audience segments.

Effective governance requires integration across temporal approaches (prebunking, in-process intervention, and debunking) within comprehensive frameworks that address platform dynamics, stakeholder collaboration, and cultural contexts. These integrated approaches must be tailored to platform-specific characteristics, coordinate across multiple platforms, involve diverse stakeholders, and remain sensitive to cultural differences in information evaluation and health beliefs.

While current research demonstrates the potential effectiveness of various governance components, significant challenges remain in developing truly adaptive governance systems. By developing a comprehensive theoretical framework of health information adoption, this study aims to provide the empirical foundation needed to design more targeted, effective, and culturally appropriate governance strategies for health misinformation on social media platforms.

2.6 Research Gap

While existing research on health-related misinformation on social media has made significant progress, several critical gaps remain that warrant further investigation:

1. Lack of Integrated Understanding of Health Information Adoption Factors (Corresponding to Research Objective 1: to explore factors influencing health information adoption on social media)

Current research lacks an integrated theoretical framework that comprehensively captures how users process and adopt health information on social media. While studies have examined individual components such as content features (Waszak et al., 2018), disseminator types (Beauvais, 2022), and user responses (Guess et al., 2020), there remains insufficient understanding of how these elements collectively influence the information adoption process. Furthermore, the psychological mechanisms underlying health information adoption, particularly how users' knowledge level and cognitive involvement affect their information processing and adoption decisions, remain unclear.

This gap is especially evident in the limited research on how these individual differences moderate information adoption in social media contexts.

2. Insufficient Theoretical Framework Development (Corresponding to Research Objective 2: to construct a theoretical framework of health information adoption on social media)

Although the Information Adoption Model has been adapted for various contexts, its application to health information on social media remains underdeveloped. Existing models like those of Cheung et al. (2008) and Erkan and Evans (2016) focus on general information or commercial content, failing to capture the unique characteristics of health information adoption. Additionally, current theoretical frameworks inadequately address the diversity of social media platforms, particularly emerging platforms with distinct features and user behaviours. The lack of a specialised theoretical framework that accounts for platform diversity and cultural variations in health information adoption necessitates the development of a more comprehensive model.

3. Limited Empirical Validation of Adoption Pathways (Corresponding to Research Objective 3: to examine the perception pathways of health information adoption)

Current research (Suarez-Lledo and Alvarez-Galvez, 2021; Wang et al., 2019) lacks comprehensive empirical validation of how different factors interact to influence health information adoption on social media. While studies have identified various influencing factors, the specific pathways through which these factors affect adoption decisions remain unclear. Particularly, there is insufficient understanding of the mediating role of perceived usefulness and how individual characteristics such as knowledge level and cognitive involvement moderate the adoption process (Pennycook and Rand, 2019; Keselman et al., 2021) (Zhao et al., 2021; Kaliyar et al., 2021). The complexity of these relationships requires sophisticated methodological approaches that can capture both direct and indirect effects in the adoption process (Erkan and Evans, 2016; Zhao et al., 2021).

4. Insufficient Integration of Theory and Practice in Governance (Corresponding to Research Objective 4: to propose governance strategies for health-related misinformation)

While existing research has examined various governance approaches, there is limited understanding of how theoretical insights about user adoption behaviour can inform practical governance strategies. This gap is particularly pronounced in cross-cultural contexts, where governance strategies may need to be adapted for different social media environments and cultural settings. Furthermore, the effectiveness of current governance approaches across different platforms and cultural contexts remains inadequately studied.

These research gaps collectively emphasise the requirements for mixed methods approaches that capture the complexities of the health information adoption process. Contemporary investigations demonstrate significant methodological limitations in their approach to understanding health information dissemination. Studies employing quantitative social media data analysis (e.g., Kaliyar et al., 2021) demonstrate high accuracy in fake news detection through deep learning approaches but may not fully capture the subtle context and motivations behind health misinformation sharing. Conversely, qualitative studies exploring user perceptions (e.g., Brashier and Schacter, 2020) provide rich insights into how factors like social changes and digital literacy affect misinformation engagement, particularly among specific demographics, but often lack generalisability. The scarcity of mixed methods approaches has resulted in a fragmented understanding of how users process and adopt health information across different platforms and cultural contexts.

Furthermore, non-Western context health misinformation research demonstrates notable limitations, particularly regarding Chinese social media environments where platform architectures, user preferences, and governance frameworks potentially differ significantly from Western counterparts. This study addresses these methodological and contextual gaps through exploratory sequential mixed methods design, enabling both adoption factor in-depth exploration and theoretical relationship validation.

This study makes several unique contributions to the field by addressing these gaps. Firstly, it develops an integrated understanding of health information adoption factors specific to social media contexts, incorporating both the mediating effects and the moderating effects. Secondly, it creates and validates a theoretical framework specifically for health information adoption that accounts for platform diversity and cultural variations. Thirdly, it empirically validates the complex pathways of influence in health information adoption through sophisticated statistical analyses. Finally, it bridges the gap between theoretical understanding and practical governance strategies, providing insights that are applicable across different cultural contexts and social media platforms.

2.7 Theoretical Basis

This study examines the evolution of the Information Adoption Model (IAM) and its various derivatives, critically analysing their applicability to social media and health information contexts.

2.7.1 Information Adoption Model and Development

The development of the Information Adoption Model (IAM) stems from in-depth research into how individuals accept, evaluate, and use information. The theoretical foundation of this model primarily derives from two important conceptual frameworks: the Elaboration Likelihood Model (ELM) (Petty and Cacioppo, 1986) and the Technology Acceptance Model (TAM) (Davis, 1989).

The Elaboration Likelihood Model (ELM), proposed by Petty and Cacioppo (1986), provides an important theoretical framework for understanding the persuasion process. This model suggests that attitude change can occur through two routes: the central route and the peripheral route. The central route involves deep cognitive processing, where individuals carefully consider the quality of arguments in the information, while the peripheral route relies on simple external cues, such as the credibility of the information source. This theoretical framework provides a foundation for understanding the mechanisms through which information influences individual decision-making processes (ibid).

Concurrently, the Technology Acceptance Model (TAM) proposed by Davis (1989) has also significantly influenced the formation of IAM. TAM emphasises the central roles of perceived usefulness and perceived ease of use in the technology acceptance process. Although IAM primarily focuses on information rather than technology, it borrows key concepts from TAM, especially the construct of perceived usefulness.

Based on these theories, Sussman and Siegal (2003) proposed the first Information Adoption Model, as shown in Figure 2.2. This model positions argument quality (corresponding to ELM's central route) and source credibility (corresponding to ELM's peripheral route) as antecedents of information usefulness, while information usefulness directly influences information adoption. This model effectively integrates the core concepts of ELM and TAM, providing a new perspective for understanding information influence in organisational environments.

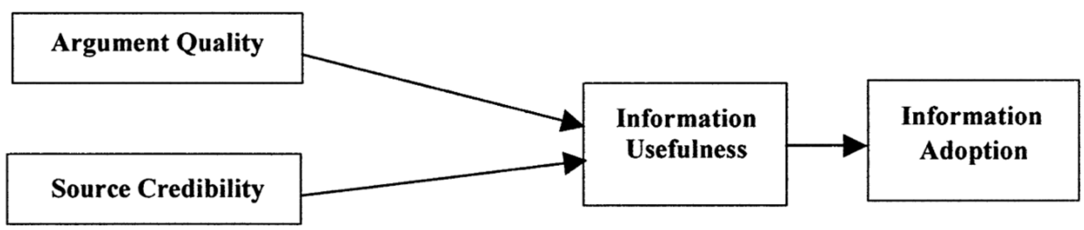

Figure 2.2: Model of Information Adoption (Sussman and Siegal, 2003, p.52)

As research deepened, Sussman and Siegal (2003) recognised the importance of individual differences in the information processing system. Based on the original model, they proposed an extended model including moderating variables, as shown in Figure 2.3. This revised model introduces expertise and involvement as moderating variables, more comprehensively explaining individual differences in the information adoption process.

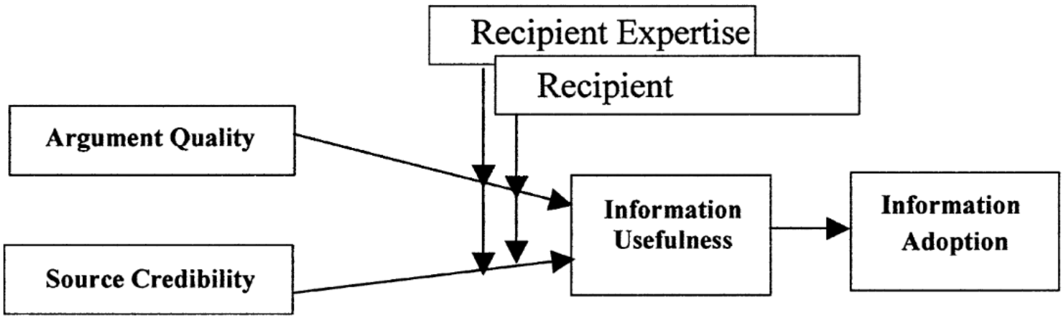

Figure 2.3: Moderated Model of Information Adoption (Sussman and Siegal, 2003, p.53)

This extension draws on Petty and Cacioppo's (1986) earlier views on ELM, namely that the recipient's expertise and involvement affect how they process information. Specifically, the recipient's expertise alters the likelihood of elaboration by influencing an individual's ability to process information. Petty and Cacioppo (1986) also point out that high recipient involvement in a topic increases the likelihood of information elaboration, while low involvement may lead to greater reliance on peripheral cues.

This revised model not only validates the effectiveness of the original IAM but also further enriches and refines the information adoption model by introducing individual difference factors. This development trajectory of IAM provides an important framework for understanding the information adoption process in different contexts.

2.7.2 Derivative Models of the Information Adoption Model

Researchers developed multiple derivative models based on the original information adoption model to adapt to different research contexts and needs.

Derivative Model 1: Online Review Adoption Model

Cheung et al. (2008), in studying the impact of electronic word-of-mouth on online consumer information adoption, further refined the constructs in the original IAM, see Figure 2.4. They subdivided argument quality into four dimensions: relevance, timeliness, accuracy, and comprehensiveness, whilst examining source expertise and source trustworthiness in terms of source credibility. The results showed that information relevance and comprehensiveness have the most significant impact on information usefulness. This finding emphasises the importance of argument quality in online environments, especially in consumer decision-making processes. The innovation of this model lies in its detailed decomposition of information quality components, providing a more refined framework for understanding how consumers evaluate online reviews.

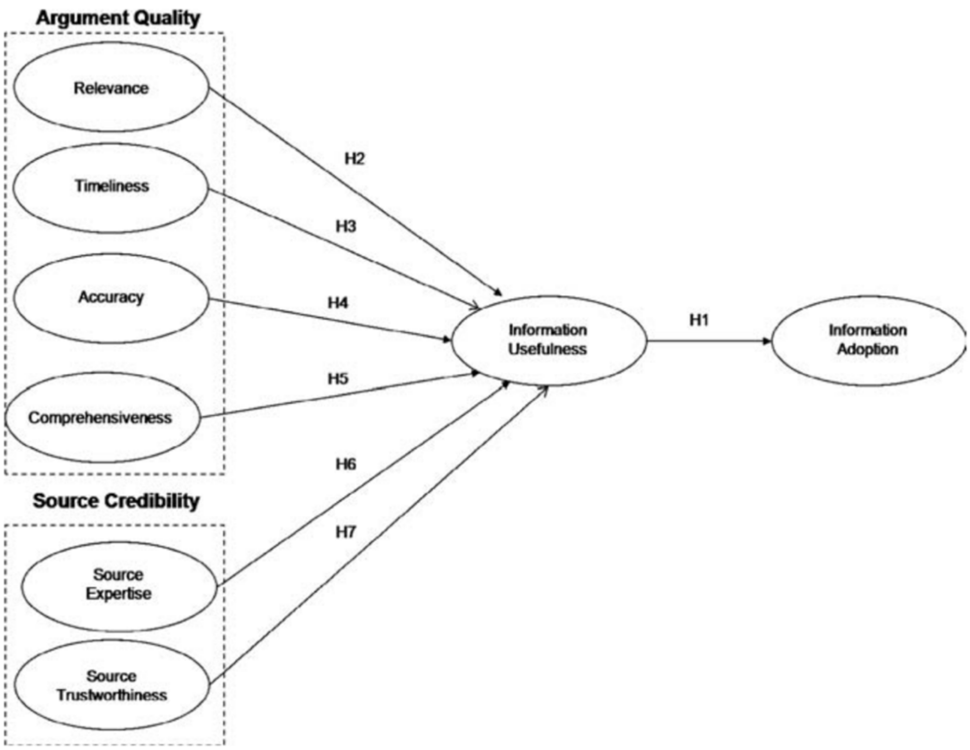

Figure 2.4: Derivative Model 1 (Cheung et al., 2008, p.233)

Derivative Model 2: Travel Website Information Adoption Model

Tseng and Kuo (2014), in studying information adoption on travel websites, added perceived risk and perceived enjoyment as two variables to the original model and specified information adoption as adoption intention, see Figure 2.5. It is worth noting that this model categorises argument quality and source credibility from the original IAM under the broader concept of information quality. This integration reflects the researcher's overall consideration of the overall quality of information, including the persuasiveness of content and source credibility. This model suggests that, in addition to perceived usefulness as a direct factor influencing adoption intention, perceived enjoyment also directly affects adoption intention. The study found that the attractiveness of website design has a significant impact on travel website information adoption, whilst the influence of perceived risk in this process is relatively small. This research extends the original model by introducing more factors related to user experience in tourism domains.

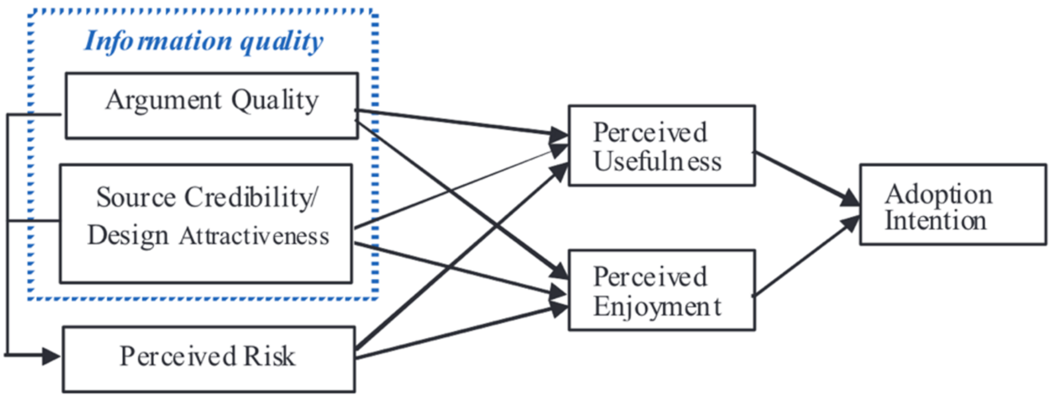

Figure 2.5: Derivative Model 2 (Tseng and Kuo, 2014, p.207)

Derivative Model 3: Electronic Word-of-Mouth Information Adoption Model

Filieri and McLeay (2014), in studying the impact of electronic word-of-mouth on travel accommodation information adoption, proposed a research model directly based on ELM, including six central routes and two peripheral routes, see Figure 2.6. In this model, timeliness, understandability, relevance, accuracy, value-added, and completeness of information it contains are considered central routes influencing information adoption, whilst information quantity and product ranking are peripheral routes of information adoption. This model further refines various aspects of information quality, providing a new perspective for understanding the influence mechanisms of electronic word-of-mouth, especially in the context of travel decision-making.

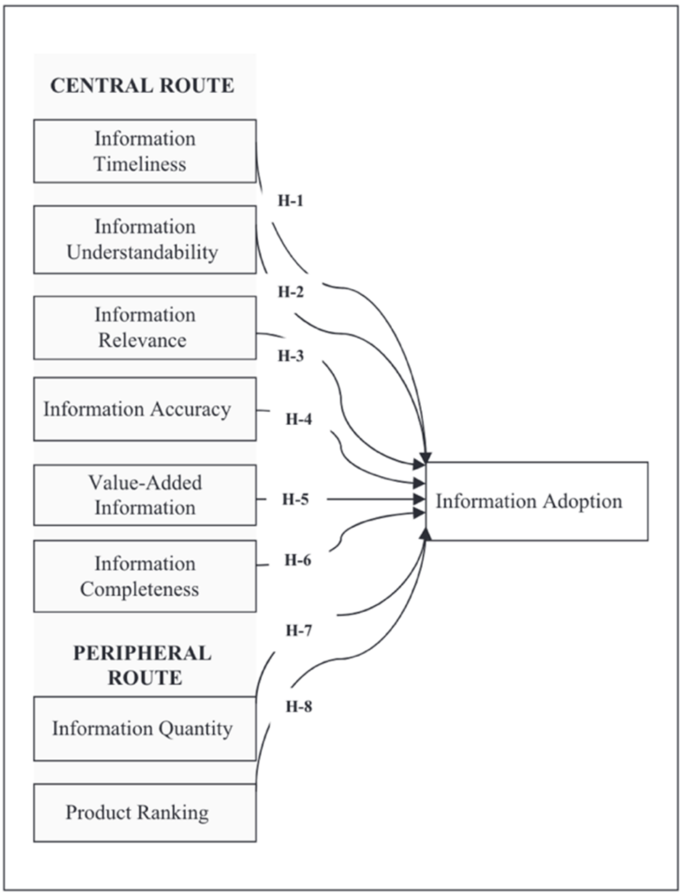

Figure 2.6: Derivative Model 3 (Filieri and McLeay, 2014, p.4)

Derivative Model 4: Social Media Electronic Word-of-Mouth Influence Model

Erkan and Evans (2016) proposed an extended information adoption model to study the impact of electronic word-of-mouth (eWOM) on social media on consumer purchase intentions, see Figure 2.7. This model integrates elements of the information adoption model and the technology acceptance model whilst introducing new constructs. Specifically, the model includes the following variables: information quality, information credibility, needs of information, attitude towards information, information usefulness, information adoption, and purchase intention. The results show that all these factors have a significant impact on consumers' purchase intentions. In particular, they found that information adoption plays a mediating role in the relationship between eWOM information and purchase intention. This study not only extends the original information adoption model but also applies it to the social media environment.

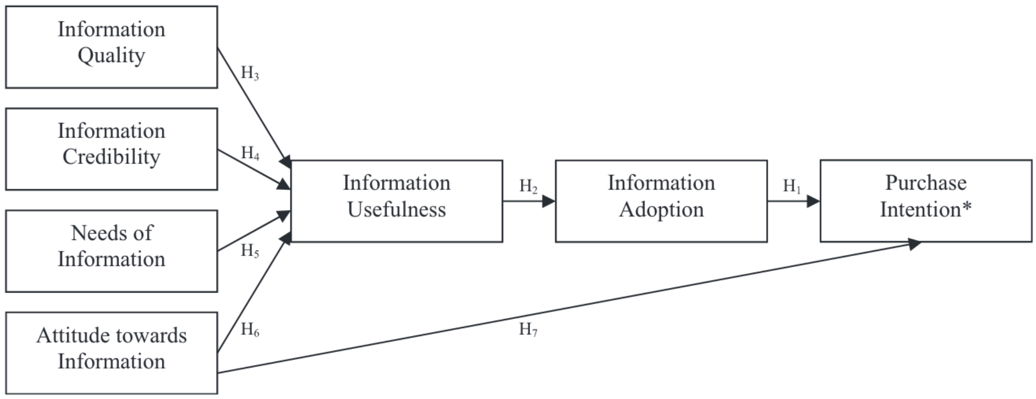

Figure 2.7: Derivative Model 4 (Erkan and Evans, 2016, p.50)

These derivative models fully demonstrate the flexibility and adaptability of the Information Adoption Model (IAM), which can be adjusted and expanded according to different research backgrounds and purposes. For example, while Cheung et al.'s (2008) model provides a detailed breakdown of information quality, it may not have fully considered the professionalism and potential risks of health information. The concept of perceived risk introduced by Tseng and Kuo (2014) may need to be more prominent and refined in the field of health information, especially considering the serious consequences that false health information may bring. Filieri and McLeay's (2014) model provides rich dimensions of information quality, but in the context of health information, it may need to further consider the timeliness, accuracy, and authority of information. Although Erkan and Evans' (2016) model is applicable to social media environments, it may need to consider more about the specificity of health information dissemination.

While the Information Adoption Model provides a valuable framework for understanding information processing, several limitations emerge when applying it to health information on social media. The model may not fully capture the unique dynamics of social media environments, where information flows are more rapid. The original IAM may also be challenged in social media contexts, where emotional responses and rapid sharing behaviours often dominate.

Furthermore, the model's treatment of source credibility as a unified construct may be insufficient for health information, where different types of expertise such as medical expertise (from healthcare professionals with formal training) and experiential expertise (from patients sharing personal health experiences) may affect information adoption in distinct ways. Research suggests that while users often rely on medical expertise for factual health information, experiential accounts from patients can sometimes be more persuasive or relatable, especially for condition-specific advice (Seymour et al., 2015; Chua and Banerjee, 2017). The original IAM also does not adequately address the role of platform algorithms in information exposure and adoption, a crucial factor in social media environments. These limitations suggest the need for significant adaptations when applying IAM to health information on social media.

Building on these important insights, this study aims to develop a theoretical framework that addresses the unique challenges of health misinformation on social media. By integrating the core constructs of information quality, source credibility, and perceived usefulness from IAM with contextual factors such as platform features and user characteristics, this study seeks to provide a more subtle and adaptive model for understanding health information adoption in the digital age. The application of this refined framework to health misinformation governance is multifaceted: information quality components help identify specific aspects of content that require verification and correction; source credibility understanding enables better design of authoritative information indicators and differentiated approaches for managing professional versus experiential health claims; and the moderating roles of knowledge level and cognitive involvement inform targeted educational interventions for different user groups.

Furthermore, the mediating role of perceived usefulness offers insights into why users might adopt misinformation despite its inaccuracy—often because it appears useful in addressing their health concerns or aligns with existing beliefs. This theoretical refinement not only advances academic understanding but also provides practical guidance for developing more effective, targeted governance strategies to combat health misinformation across diverse social media platforms and cultural contexts.

2.8 Chapter Summary

This chapter provides a literature review on health-related misinformation on social media, beginning with fundamental definitions and classifications, proceeding through dissemination mechanisms and governance approaches, and culminating in the identification of critical research gaps and theoretical basis.

Firstly, existing research lacks a holistic analysis of the health information dissemination process. While studies have examined the characteristics of information itself (including content features and emotional elements), disseminator types (both well-intentioned and malicious), and recipient factors (such as demographic characteristics and cognitive abilities), most tend to focus on these elements in isolation. This partial research approach limits the comprehensive understanding of how these components interact in social media environments. Therefore, this study emphasises the need for a more integrated approach, considering these three key elements and their interactions simultaneously, to fully grasp the complexity of health information adoption.

Secondly, limitations in research methods also become constraining factors. Most existing studies adopt a single qualitative or quantitative method, making it difficult to fully reflect the multidimensional characteristics of health information adoption in social media environments. Qualitative research, while providing in-depth insights, is often difficult to generalise; quantitative research, although capable of large-scale analysis, may lack depth. These methodological limitations highlight the necessity of adopting mixed research methods. By combining qualitative and quantitative methods, this study aims to obtain more comprehensive and in-depth research results, thereby more accurately portraying the full picture of health information adoption on social media.

Moreover, existing research lacks sufficient attention to non-Western social media platforms, especially regarding health information dissemination on Chinese platforms such as WeChat, Douyin, and Weibo. The unique characteristics and user behaviour patterns of these platforms, including closed social circles, algorithmic content distribution, and platform-specific features, may significantly influence the dissemination and adoption of health information, warranting in-depth exploration. This study focuses on the Chinese social media environment, filling this research gap and providing new perspectives for understanding health information dissemination in different cultural contexts.

Regarding theoretical foundations, the Information Adoption Model (IAM) and its derived models provide important conceptual frameworks for this study. Although these models emphasise key factors such as information quality, source credibility, and perceived usefulness in the information adoption process, they require adaptation to fully address the unique characteristics of health information dissemination on social media platforms. These core concepts provide theoretical guidance for analysing health information adoption while acknowledging the need for contextual adaptation.

This comprehensive literature review not only identifies crucial research gaps but also provides the theoretical and methodological foundation for examining health information adoption on social media platforms. The next chapter will detail the exploratory sequential mixed methods adopted in this study.

Chapter 3 Methodology

3.1 Overview

This chapter begins by detailing the research paradigm and philosophical foundations, including the ontological, epistemological, axiological, and methodological positions that guide the study. It then introduces the rationale for selecting a mixed methods research approach, specifically an exploratory sequential design that combines inductive and deductive approaches. The chapter elaborates on the specific application of pragmatic mixed methods with a social constructivist stance in this study, detailing how the sequential implementation of qualitative and quantitative phases enables the exploration of the complex phenomenon of health misinformation dissemination while maintaining philosophical and methodological coherence.

3.2 Research Paradigm and Philosophy

A research paradigm represents a fundamental belief system or worldview that guides scientific inquiry, including assumptions about the nature of reality, knowledge, and research methodology (Guba and Lincoln, 1994). Thomas Kuhn first proposed the concept of 'paradigm' in 'The Structure of Scientific Revolutions', defining it as a set of beliefs, values and techniques shared by the scientific community (Kuhn, 1962). Paradigms not only influence how researchers view the world but also determine how they understand and study it (Creswell, 2014). The selection of an appropriate research paradigm is particularly crucial when studying health information dissemination on social media, given the complex interplay between technological, social and behavioural factors.

There are four main paradigms in social science research: positivism, post-positivism, constructivism, and critical theory (Denzin and Lincoln, 2011). Each paradigm has its distinct ontological, epistemological, axiological, and methodological positions. The choice of paradigm significantly influences research design, data collection methods, and interpretation of findings (Crotty, 1998).

This study adopts a research paradigm that integrates elements of social constructivism and pragmatism, as neither paradigm alone can fully capture the complexity of health information dissemination on social media. This integration creates a complementary philosophical framework where social constructivism enables deep exploration of how users collectively construct meaning from health information through their interactions, while pragmatism ensures that the research maintains its focus on developing actionable solutions for managing health misinformation. This combination is particularly valuable in the social media context, where meaning construction occurs through complex social interactions, yet there is a pressing practical need to address misinformation challenges (Morgan, 2014b). The following explain the philosophical stance of this study through four interconnected aspects: ontology, epistemology, axiology, and methodology.

3.2.1 Ontology

Ontology concerns the nature of reality and its form of existence, exploring 'what is existence, what is reality' (Guba and Lincoln, 1994) and 'what is real' (Crotty, 1998). In social science research, ontological positions shape how researchers conceptualise their research objects and interpret their findings (Holstein and Gubrium, 2008). There are two main ontological positions in social science research: realism (or objectivism) and relativism (or subjectivism) (Bryman, 2012). Realism holds that social reality exists objectively, independent of individual cognition and understanding (Cohen et al., 2011). Relativism believes that reality is subjective, constructed by individual or group cognition and interpretation (Guba and Lincoln, 1994).

This study adopts the ontological position of social constructivism. Social constructivism believes that reality is constructed through social interaction and consensus (Berger and Luckmann, 1966). This position is particularly suitable for studying health information dissemination on social media, where meaning is co-created and negotiated by users through interaction (Morgan and Smircich, 1980). The social constructivist perspective acknowledges that while scientific facts about health may exist independently, such as the scientific accuracy of certain health information, their interpretation and significance are shaped by social processes and cultural contexts (Schwandt, 2000).

In the context of this study, the social constructivist position means that the meaning and value of health information on social media are not inherent or absolute but are continuously formed and reshaped in user interactions and interpretations (Holstein and Gubrium, 2008). This dynamic process involves multiple stakeholders, including healthcare professionals, content creators, and general users, who collectively contribute to the construction of health information meaning. The credibility of health information is determined not only by its content but also by user engagement, sharing patterns, and social discourse. Moreover, users' understanding, and adoption of health information are formed in specific social and cultural contexts, influenced by personal experiences, social norms, and cultural values.

This ontological position enables the research to focus on the dynamic dissemination process of health information in the social media environment. It provides a theoretical framework for understanding how different social actors contribute to the construction and interpretation of health information meaning (Schwandt, 2000). It allows exploration of how users construct their understanding and attitudes towards health information through social interaction and how different groups, such as ordinary social media users, health professionals, and so on, collectively construct the meaning and importance of health information.

3.2.2 Epistemology

Epistemology concerns the nature of knowledge and how it is acquired. It focuses on the nature, source, and limits of knowledge and explores the question of 'how we know what we know' (Crotty, 1998). This philosophical dimension is crucial in social science research as it guides how researchers approach knowledge generation and validation

(Denzin and Lincoln, 2011). The main epistemological positions include objectivism, subjectivism, and constructivism (Creswell, 2014).

This study adopts a pragmatic epistemological stance. Pragmatism holds that the value of knowledge lies in its practical application and problem-solving ability (Morgan, 2014b). This position maintains that truth is relative to its practical effectiveness (Biesta, 2010). In pragmatic research, the focus shifts from abstract philosophical questions about the nature of truth to practical concerns about how knowledge can inform action and improve practice (Johnson and Onwuegbuzie, 2004). In the context of health information dissemination on social media, the pragmatic stance focuses on both understanding this phenomenon and formulating practical improvement strategies.

The application of pragmatic epistemology in this study is reflected in several aspects. Firstly, the research goal is not only to understand the mechanisms of health information dissemination on social media but also to explore how to improve the dissemination and adoption of health information effectively. Secondly, the method selection allows the flexible use of qualitative and quantitative methods to obtain the most valuable research results. For example, in-depth qualitative interviews are used to understand users' perceptions and attitudes towards health information, while quantitative surveys are used to test the generalisability of these findings. Based on these complementary research approaches, the value of research results lies not only in their theoretical contribution but also in their guiding significance for improving the practice of health information dissemination on social media.

This epistemological stance is consistent with the mixed methods adopted in this study (Tashakkori and Teddlie, 2010). It provides a philosophical foundation for combining different research approaches while maintaining methodological rigour (Greene, 2007). It allows flexible selection and integration of different research methods and data types according to the needs of research questions, thereby comprehensively exploring health information dissemination on social media.

3.2.3 Axiology

Axiology concerns research values and ethical issues, exploring whether research should be value-neutral or value-laden (Creswell, 2014). In social science research, complete value neutrality is almost impossible, as researchers' values and beliefs inevitably influence various stages of research (Cohen et al., 2011). The acknowledgement of value influence does not diminish research rigour but rather enhances transparency and trustworthiness (Maxwell, 2012). This study adopts a balanced axiological stance, maintaining objectivity whilst acknowledging the inherent influence of personal values and experiences in the research process.

The axiological goal of this study is to mitigate the negative impact of false health information on social media and promote the circulation of accurate information to improve public health awareness and social well-being. This goal reflects both the social responsibility and practical significance of the research, particularly in an era where social media significantly influences public health beliefs and behaviours. The emphasis on social benefit aligns with the study's pragmatic orientation while maintaining academic rigour (Greene, 2007).

The researcher maintains transparency about potential biases and limitations, particularly when dealing with sensitive health information. This approach ensures that while personal values inevitably influence the research process, their impact is acknowledged and managed through rigorous methodological procedures (Greene, 2007). The research maintains a careful balance between academic rigour and practical utility, to provide both theoretical insights and actionable recommendations for improving the social health information environment.

3.2.4 Methodology

Methodology provides the strategic framework for selecting and implementing research methods, guiding the entire research process (Crotty, 1998). While methods refer to specific data collection and analysis techniques, methodology includes the broader principles that guide these choices (Denzin and Lincoln, 2011). This study adopts a mixed methods approach, specifically an exploratory sequential design, integrating the strengths of both qualitative and quantitative research traditions (Creswell and Plano Clark, 2011). This methodological choice reflects the complex nature of health information dissemination on social media and aligns with the study's pragmatic philosophical orientation.

The methodological framework aligns with the study's philosophical foundations. The social constructivist ontology guides the qualitative exploration of how users construct meaning from health information, while the pragmatic epistemology supports the use of quantitative methods to verify and expand these understandings (Morgan, 2014b). This integration of approaches acknowledges that different aspects of health information dissemination may require different investigative methods.

Qualitative data collection and analysis follow established protocols for ensuring trustworthiness, while quantitative methods adhere to statistical validity and reliability requirements (Onwuegbuzie and Johnson, 2006). This dual approach helps ensure that the research findings are credible and applicable to real-world contexts. This methodological approach allows the research to capture the depth and breadth of health information dissemination on social media.

In summary, this study's philosophical framework integrates social constructivist ontology, pragmatic epistemology, balanced axiology, and mixed methods methodology to create a comprehensive research paradigm (Creswell and Plano Clark, 2011). This integration acknowledges both the socially constructed nature of health information meaning making on social media and the practical imperative to address misinformation challenges. The framework provides a coherent foundation for investigating both the theoretical and practical aspects of health information dissemination (Morgan, 2014a). The social constructivist ontological position enables understanding of how users collectively create and interpret health information, whilst the pragmatic epistemological stance ensures research outcomes have practical utility. The balanced axiological approach maintains research rigour while acknowledging value influences, and the mixed methods methodology provides the technical framework for a comprehensive investigation.

3.3 Methodological Choice

The selection of appropriate research methods plays a crucial role in addressing research questions effectively and ensuring the quality of research findings (Bryman, 2012). This methodological decision reflects the researcher's philosophical position and establishes the framework for data collection, analysis, and interpretation (Creswell, 2014). In social science research, three main methodological choices are available: mono method, multiple methods, and mixed methods (Teddlie and Tashakkori, 2009).

3.3.1 Mono Method

Mono method research refers to using a single methodological approach throughout the research process, either exclusively quantitative or qualitative (Bryman, 2012). Each approach serves different research purposes and is based on distinct philosophical assumptions.

Qualitative mono method research typically aligns with interpretivism and constructivism, focusing on a deep understanding of social phenomena and human experiences (Denzin and Lincoln, 2011). Data collection often occurs through interviews, focus groups, or field observations. The primary strength of qualitative methods lies in their ability to reveal complex social processes and explore the detailed contexts of human behaviour (Patton, 2002). However, Maxwell (2013) highlights several limitations, including challenges with generalisability due to smaller sample sizes, the time-intensive nature of data collection and analysis, and potential researcher bias during interpretation.

Quantitative mono method research aligns with positivist traditions and emphasises measurement and testing relationships between variables (Creswell, 2014). This approach commonly employs surveys, experiments, or structured observations to collect numerical data for statistical analysis. While quantitative methods excel at testing hypotheses and establishing statistical relationships across large samples, they face certain limitations. Guba and Lincoln (1994) argue that quantitative approaches may oversimplify complex social phenomena and miss important contextual refinements. Furthermore, predefined response categories might not capture unexpected or emerging aspects of social phenomena.

3.3.2 Multiple Methods

Multiple methods research involves using two or more data collection techniques within either a quantitative or qualitative framework (Bryman, 2012). This approach differs from mixed methods as it remains within one methodological paradigm while utilising different data collection strategies.

In multiple qualitative methods could combine individual interviews with focus group discussions or merge participant observation with document analysis. Similarly, multiple quantitative methods allowed researchers might combine online surveys with experimental designs or integrate secondary data analysis with primary data collection. The main advantage of this approach lies in its ability to enhance data triangulation within a consistent methodological framework (Denzin, 2012). However, Morse (2003) argues that while multiple methods can offer richer insights than mono method approaches, they remain constrained by the limitations of their underlying methodological paradigm.

3.3.3 Mixed Methods

Mixed methods research represents a more comprehensive approach, combining both quantitative and qualitative methods within a single research design (Creswell and Plano Clark, 2011). This methodology has gained increasing prominence in social science research, particularly for investigating complex phenomena that require both detailed understanding and broader generalisation (Johnson et al., 2007).

Three primary method designs exist (Creswell and Plano Clark, 2017). First, the convergent parallel design involves simultaneous collection and analysis of both types of data, followed by result integration. This approach effectively compares different perspectives but demands significant resources for concurrent data collection (Fetters et al., 2013). Second, the explanatory sequential design begins with quantitative research, followed by qualitative investigation to explain or elaborate on the quantitative results. This approach proves valuable for explaining unexpected quantitative results but may be less suitable when initial exploration is necessary (Ivankova et al., 2006). Third, the exploratory sequential design begins with qualitative research to explore a phenomenon, followed by quantitative research to test or generalise the initial findings. This design particularly suits situations where important variables need identification or when researchers aim to develop and test instruments based on qualitative findings (Morgan, 2014a).

Mixed methods research offers several advantages over mono method approaches, providing more comprehensive evidence for studying research problems (Teddlie and Tashakkori, 2009). Through methodological triangulation, it enhances the validity and reliability of findings (Denzin, 2012). However, mixed methods research also presents challenges, requiring researchers to be proficient in both methodological approaches and effectively integrate different data types (Johnson and Onwuegbuzie, 2004).

3.3.4 Rationale of the Mixed Methods Used in the Study

This study adopts an exploratory sequential mixed methods design, a choice driven by both the research problem’s nature and the study’s specific objectives. The complexity of health information dissemination on social media, involving multiple dimensions of user behaviour, information characteristics, and platform mechanisms, necessitates a comprehensive methodological approach capturing both depth and breadth of understanding.

The complex nature of health misinformation dissemination on social media is still relatively unexplored, making it necessary to begin with qualitative investigation to identify relevant variables and understand contextual factors. The qualitative phase helps discover how users interpret and respond to health information, which cannot be predetermined through existing theories alone.

The convergent parallel design proved less suitable because understanding health misinformation dissemination first requires deep qualitative exploration to identify relevant variables and understand contextual factors. This is particularly important given the dynamic nature of health misinformation on social media, where user behaviours and platform mechanisms are constantly evolving.

Similarly, the explanatory sequential design was rejected because the study aims first to explore and understand the factors influencing health information adoption before testing their relationships quantitatively. The exploratory nature of this study requires an initial qualitative phase to discover the subtle ways in which users engage with and share health information on social media platforms.

Additionally, the study aims to develop a comprehensive theoretical framework that can be tested quantitatively. The sequential nature of the design allows the qualitative findings to directly inform the development of survey instruments and hypotheses for the quantitative phase, ensuring that the measurements are grounded in users' actual experiences and perspectives. This is especially crucial in the context of health misinformation, where multiple factors, including information quality, source credibility, and platform characteristics, influence users' information adoption behaviours.

The exploratory sequential design aligns with the study's objectives through a two-phase approach with clear integration mechanisms. The initial qualitative phase, employing in-depth interviews and social media comment analysis, enables deep exploration of how users interact with health information on social media. These qualitative insights directly inform the development of the quantitative survey instrument through a structured transition process where key themes and constructs identified from interviews and comments are systematically transformed into measurable variables and survey items. This direct integration ensures that the quantitative phase is firmly grounded in participants' actual experiences rather than solely on theoretical assumptions.

The integration between phases occurs at multiple levels: theoretical constructs identified in qualitative analysis directly shape the theoretical model tested in the quantitative phase; specific language and terminology used by participants inform questionnaire wording; and the relationships between factors observed in qualitative data guide hypothesis formulation. This methodological choice facilitates what Greene et al. (1989) term 'development', where qualitative phase results enhance the validity and relevance of the quantitative phase. The combination also enables 'complementarity', where qualitative findings provide context and explanatory power to quantitative results, while quantitative data establish the prevalence and relationships among identified factors.

Furthermore, this design aligns well with the study's social constructivist stance in the initial phase, while the subsequent quantitative phase satisfies the pragmatic need to verify findings across a larger population and develop practical governance recommendations.

The selection of a mixed methods approach for this study goes beyond methodological preference to address the fundamental complexity of health information dissemination on social media platforms. Social media health information adoption involves multiple layers of complexity that cannot be adequately captured through either qualitative or quantitative methods alone.

A mono-method qualitative approach, while providing contextual insights into user experiences, would limit our ability to test and verify relationships between identified variables across larger populations. Similarly, a purely quantitative approach would risk overlooking the subtle social, cultural, and personal contexts that shape how individuals interpret and respond to health information online.

The exploratory sequential design specifically addresses the contextual complexity of Chinese social media environments, where health information flows through unique platform architectures and cultural communication patterns. The qualitative phase allows for cultural and contextual sensitivity in identifying relevant variables, while the subsequent quantitative phase enables testing of these insights across a broader population.

Furthermore, the integration of methods in this study goes beyond simply combining different data types. The sequential integration allows qualitative findings to directly inform quantitative instrument development, ensuring cultural and contextual relevance of measurement items. This approach creates a synergistic relationship between methods, where qualitative insights enhance the validity and relevance of quantitative measurements, while quantitative data provides validation and generalisability of qualitative findings.

This methodological integration is particularly crucial when studying health information on social media in China, where platform-specific features, regulatory environments, and cultural communication patterns create unique dynamics that have not been extensively studied in previous research.

3.4 Research Approaches

This study employs both inductive and deductive approaches in a sequential manner to investigate health misinformation dissemination on social media platforms (Creswell and Plano Clark, 2011). This integration enables a comprehensive understanding of the complex phenomena while maintaining methodological rigour throughout the research process (Morgan, 2007).

3.4.1 Inductive Approach

The inductive approach is primarily employed in the qualitative phase of this study, forming the foundation for theory development through systematic analysis of user experiences and behaviours (Thomas, 2006). Through semi-structured interviews with social media users and analysis of social media comments, this approach enables the identification of key factors influencing health information adoption (Gioia et al., 2013). The process involves systematic coding of interview transcripts and social media comments, allowing patterns and themes to emerge from the data (Miles et al., 2013). These emerging patterns help develop theoretical constructs about how users evaluate and adopt health information on social media platforms. Following Charmaz's (2006) constructivist grounded theory approach, the inductive phase culminates in the construction of a theoretical framework that explains the relationships between the identified factors, providing a foundation for the subsequent quantitative investigation.

3.4.2 Deductive Approach

Following the qualitative phase, the deductive approach is applied to test and validate the theoretical framework developed through the inductive analysis (Hyde, 2000). This phase begins with the development of specific hypotheses based on the qualitative findings, followed by the operationalisation of theoretical constructs into measurable variables (Edwards and Berry, 2010). A questionnaire survey is then designed and conducted to collect quantitative data from a larger sample of social media users. Through sophisticated statistical techniques, including structural equation modelling and path analysis (Hair et al., 2010), the hypothesised relationships between variables are tested, enabling the validation and refinement of the theoretical framework. This systematic testing of hypotheses helps establish the generalisability of the qualitative findings while maintaining analytical rigour (Spector, 2006).

3.4.3 Integration of Approaches

The integration of inductive and deductive approaches in this study represents a thoughtful response to the complex nature of health information dissemination on social media (Maxwell and Mittapalli, 2010). The qualitative findings directly inform the development of the quantitative survey instrument, ensuring its relevance and validity in measuring the identified constructs (Greene et al., 1989). Conversely, the statistical analysis provides validation of the qualitative insights while enabling generalisation to a broader population (Teddlie and Tashakkori, 2009). This complementary relationship between approaches enables both contextual understanding and statistical verification, resulting in a more comprehensive and subtle understanding of health information dissemination mechanisms. Following Denzin's (2012) guidance on methodological integration, the sequential implementation of these approaches ensures methodological coherence while maximising the strengths of both qualitative and quantitative research paradigms.

3.5 Application of Pragmatic Mixed Methods with a Social Constructivist Stance

This study adopts a pragmatic mixed methods approach with a social constructivist stance, reflecting the complexity and multifaceted nature of health information dissemination on social media. Pragmatism provides a philosophical foundation that allows researchers to select methods based on their effectiveness in addressing research problems rather than adherence to a single philosophical position (Morgan, 2014b). Tashakkori and Teddlie (2010) argue that pragmatism particularly suits mixed methods research by enabling the flexible use of both qualitative and quantitative methods to achieve comprehensive research outcomes.

The social constructivist stance complements this pragmatic approach by emphasising that knowledge and reality are constructed through social interaction and consensus (Berger and Luckmann, 1966). This perspective holds particular relevance for understanding how individuals' interpretation and adoption of health information are influenced by their social and cultural backgrounds, personal experiences, and group interactions. As Creswell (2014) notes, social constructivism proves especially valuable when exploring how people understand and ascribe meaning to their experiences, making it particularly suitable for examining how social media users perceive, evaluate, and adopt health information within their social contexts.

The integration of pragmatism and social constructivism manifests in the study's exploratory sequential mixed methods design. The qualitative stage employs semi-structured interviews and social media comment analysis to explore factors influencing health information adoption. Semi-structured interviews allow flexible investigation of participants' experiences and viewpoints while maintaining consistency across different interviews. Simultaneously, social media comment analysis captures users' authentic responses in natural environments, providing valuable insights into their real-world interactions with health information.

The quantitative stage builds directly upon qualitative findings, transforming identified factors into measurable variables and testable hypotheses through a large-scale questionnaire survey. This stage employs sophisticated statistical techniques, including descriptive statistics, factor analysis, and Structural Equation Modelling (Hair et al., 2010), to systematically examine relationships between variables and test the theoretical framework developed from qualitative insights. The survey instrument's design draws directly from qualitative findings, ensuring its relevance and validity in measuring the identified constructs.

The analytical framework reflects the integration of both methodological approaches. Qualitative data undergoes rigorous analysis using grounded theory (Corbin and Strauss, 2008), with systematic coding procedures refining core categories. The subsequent quantitative analysis provides statistical validation of these constructs while enabling generalisation to a broader population. This complementary analytical strategy ensures both depth of understanding and breadth of application.

This integrated methodological approach overcomes the limitations inherent in mono method studies while maintaining philosophical coherence. The social constructivist stance guides the exploration of how users collectively create meaning from health information, while the pragmatic orientation ensures the research produces actionable insights for addressing health misinformation challenges.

3.6 Chapter Summary

This chapter has systematically outlined the methodological framework adopted in this study, which integrates elements of pragmatism and social constructivism to investigate the dissemination mechanisms and governance of health-related misinformation on social media.

The chapter began by discussing the research paradigm and philosophical foundations, clarifying the ontological, epistemological, axiological, and methodological positions that underpin the study. The social constructivist ontology, which views reality as socially constructed, is combined with the pragmatic epistemology that emphasises the practical utility of knowledge. This philosophical stance is reflected in the balanced axiological approach, which acknowledges the influence of researcher values while maintaining academic rigour.

The rationale for selecting a mixed methods research design, specifically an exploratory sequential approach, was then examined. This methodological choice enables the study to deeply explore the complex, context-dependent phenomena of health information dissemination through qualitative inquiry and then validate and generalise these insights through quantitative investigation. The integration of inductive and deductive research approaches further strengthens the study's ability to build theory and test hypotheses in a complementary manner.

A core element of this study's methodological framework is the application of pragmatic mixed methods with a social constructivist stance. This approach allows the researcher to flexibly employ qualitative and quantitative techniques to comprehensively understand how social media users construct and interpret health information's meaning and importance. The sequential implementation of these methods ensures that the qualitative and quantitative phases inform and enrich each other, resulting in a more holistic and subtle understanding of the research problem.

The methodological framework established in this chapter provide the foundation for detailed research design presented in the next chapter. The integration of social constructivist and pragmatic approaches informs the selection and implementation of specific research methods. Chapter 4 will detail the practical application of this framework through qualitative methods (semi-structured interviews and social media comment analysis) and quantitative methods (survey questionnaire). It will outline the sampling strategies, data collection procedures, and analytical techniques that align with both the inductive exploration of users' health information interpretation processes and the deductive testing of the resulting theoretical framework. it will also address the quality assurance measures and ethical considerations necessary for investigating health information dissemination in social media contexts.

Chapter 4 Methods

4.1 Overview

This chapter provides a detailed explanation of the mixed research methods employed in this study. This chapter begins by introducing the qualitative and quantitative research designs, including the rationale for using interviews, comment extraction, and online surveys. It then clarifies the data collection process, sampling strategies, and research tool design, as well as the data analysis of qualitative and quantitative data. Finally, it discusses measures to ensure research quality and ethical considerations.

4.2 Research Design

This study employs an exploratory sequential mixed methods design, which begins with qualitative research followed by quantitative investigation. This approach aligns with the research objectives of first exploring and understanding the mechanisms of health information adoption on social media and then developing and testing a theoretical model.

4.2.1 Qualitative Research Design

The qualitative phase of this research serves two primary purposes: to explore factors influencing health information adoption on social media, then to provide foundational insights for quantitative model development. This study employs two complementary qualitative data collection methods: semi-structured interviews and social media comment extraction.

4.2.1.1 Semi-Structured Interviews

Semi-structured interviews are a primary method for gathering detailed data about individuals' experiences and perspectives regarding health information on social media. This method is particularly suitable for grounded theory research as it allows themes to emerge naturally from participants' narratives while maintaining sufficient structure to ensure relevant topics are covered (Glaser and Strauss, 1967).

The interview process was carefully designed to align with grounded theory principles, where the researcher approaches the field with an open mind rather than predetermined theoretical frameworks. The interview guide focused on three main understanding of users' (1) perception, (2) discrimination and (3) behavioural tendencies towards health information. These areas were explored through open-ended questions, allowing participants to guide the conversation towards aspects they found most relevant (Patton, 2002).

The twelve participants were purposively selected through a systematic process to represent diverse occupational backgrounds relevant to the research context. Following a theoretical sampling approach (Charmaz, 2014), participants were purposefully chosen to provide varying perspectives on health information engagement. The selection process began with identifying individuals from four key stakeholder groups: healthcare professionals, media practitioners, academics, and general public users with varying degrees of health literacy. Within each category, potential participants were evaluated based on their regular social media usage, experience with health information on these platforms, and their ability to articulate their experiences.

Theoretical saturation guided the determination of adequate sample size. The process involved continuous assessment of emerging data patterns during concurrent data collection and analysis. After conducting eight initial interviews, preliminary analysis identified key emerging themes. Four additional interviews were then conducted with specific attention to whether new insights continued to emerge. Saturation was determined through three indicators: (1) consistent patterns appearing across multiple interviews, (2) diminishing appearance of new codes in successive interviews, and (3) sufficient depth in the identified concepts. By the twelfth interview, core categories had stabilised with no substantial new themes emerging, confirming theoretical saturation had been achieved in line with the sampling approach further detailed in 4.4.1.

The interviews were conducted through both online and face-to-face formats, adapting to participant preferences and practical considerations. This flexibility in the interview format proved beneficial for several reasons. Online interviews, conducted via video conferencing platforms, enabled participation from geographically distant individuals and accommodated diverse schedules. Face-to-face interviews, held in quiet locations chosen by participants, facilitated deeper rapport building. Both formats yielded detailed information, with online interviews particularly appropriate given the study's focus on social media behaviour (Archibald et al, 2019).

Each interview session lasted between 45-90 minutes, allowing sufficient time for in-depth exploration while maintaining participant engagement. The interviews began with general questions about social media usage, gradually moving to more specific queries about health information encounters and decision-making processes. This funnelling technique helped establish rapport and allowed participants to become comfortable before discussing more detailed aspects of their experiences (Holstein and Gubrium, 1995).

4.2.1.2 Online Comment Extraction

To complement the interview data, this study incorporates natural user interactions by extracting and analysing social media comments related to health information. This approach provides access to spontaneous, unfiltered user responses in their natural online environment (Silverman, 2016).

The comment extraction process focused on three major Chinese social media platforms: WeChat, Douyin, and Weibo. These platforms were selected for their significant user base and diverse health information content. Comments were collected from health-related posts that received substantial user engagement. The extraction process utilised manual collection methods, gathering comments from posts published within a year period.

Selection criteria for comments included relevance to health information, substantive content, beyond simple expressions like ‘good’ or emoticons, and absence of spam or inappropriate content. Comments were collected from various health topics to ensure broad coverage of user perspectives and reactions.

Special attention was paid to ethical considerations during comment extraction. All collected data was anonymised, with personal identifiers removed. The focus remained on publicly available comments; no private or protected information was accessed. This approach balances research needs with ethical requirements for social media research (Davies, 2014).

4.2.1.3 Rationale for Using Interviews and Online Comments

The combination of semi-structured interviews and online comment analysis represents a comprehensive approach to understanding health information adoption on social media. This dual-method approach provides complementary perspectives: interviews offer deep insights into individual experiences and decision-making processes, while comment analysis captures natural user behaviours and reactions in the social media environment.

Semi-structured interviews allow for detailed exploration of personal experiences and thought processes, providing context and depth to understanding how individuals evaluate and adopt health information. The interview format enables probing of complex decision-making processes and allows participants to elaborate on their experiences in ways that might not be apparent in their online behaviours (Holstein and Gubrium, 1995).

Conversely, social media comments provide access to naturalistic data, capturing user reactions and behaviours in their actual social media context. This data is particularly valuable as it represents spontaneous responses unaffected by research settings or interviewer presence (Silverman, 2016). The large volume of comment data also helps identify patterns and trends that might not be apparent from interview data alone.

The combination of these two methods creates a methodological triangulation, enhancing the credibility and comprehensiveness of the study findings (Denzin, 1978). While interviews provide depth and context, comment analysis offers breadth and naturalistic insights. This complementarity helps overcome the limitations of each method individually: interviews might be subject to recall bias or social desirability effects. At the same time, social media comment analysis might lack a contextual understanding of user motivations.

4.2.2 Quantitative Research Design

The quantitative phase of this research serves two primary purposes: to validate the theoretical framework derived from qualitative findings and to examine the relationships between factors influencing health information adoption on social media platforms. Quantitative methods are particularly valuable for testing hypotheses and establishing generalisable patterns in social science research (Creswell and Creswell, 2018).

4.2.2.1 Online Questionnaire

The online questionnaire serves as the primary instrument for quantitative data collection in this study. This method was chosen for its ability to systematically collect large-scale data suitable for statistical analysis and hypothesis testing (Hair et al., 2018). The questionnaire design follows a rigorous process informed by both the qualitative findings and the validated scale.

While existing scales in information adoption research provided valuable reference points, the measurement items were primarily developed based on qualitative findings to capture the unique characteristics of health information adoption in social media contexts (DeVellis, 2017). This approach was chosen because health information processing may differ significantly from general information adoption behaviours, requiring context-specific measurements (Wicks, 2004).

A preliminary pilot study with 120 participants was conducted to assess the questionnaire's reliability and validity. Exploratory Factor Analysis (EFA) was employed to evaluate the construct validity and internal consistency of the scales (Tabachnick and Fidell, 2019). Based on the pilot study results, necessary refinements were made to improve item clarity and measurement accuracy.

4.2.2.2 Rationale for Using Online Surveys

The choice of online surveys as the quantitative data collection method was driven by several methodological and practical considerations. First, online surveys provide an ideal match with the research context, as the study focuses on social media users and their online behaviours, enhancing ecological validity (Sue and Ritter, 2012). Second, online surveys offer advantages in terms of reach and accessibility. They enable efficient access to a large, diverse sample of social media users, which is crucial for testing the theoretical model and ensuring the generalisability of findings (Fowler, 2014). The digital nature of online surveys allows participants to complete the questionnaire at their convenience, potentially increasing response rates and data quality. The anonymity provided by online surveys is particularly valuable for health-related research. When discussing health information behaviours, participants may be more candid in their responses when assured of anonymity, helping to reduce social desirability bias (Tourangeau et al., 2013). Furthermore, online surveys offer practical benefits in terms of data quality and management, as digital data collection minimises data entry errors and enables immediate data validation checks (Dillman et al., 2014). This is also an environmentally friendly method.

4.3 Data Collection

This study employs an exploratory sequential mixed methods data collection strategy to investigate health information dissemination on social media platforms. The data collection process consists of three main components: semi-structured interviews, extraction of social media comments, and an online questionnaire survey.

4.3.1 Data Collection Framework

This study utilises both primary and secondary data sources to achieve methodological triangulation. Primary data comprises original information obtained directly from participants through semi-structured interviews and online survey questionnaires (Bryman, 2016). These data sources provide current, relevant information that directly addresses the research questions, particularly regarding individual perceptions and behaviours related to health information on social media platforms.

Secondary data, particularly user comments extracted from social media platforms, complements the primary data collection by providing naturalistic expression patterns and reducing social desirability bias (Ruths and Pfeffer, 2014). The integration of both data types enables a comprehensive understanding of health information dissemination patterns whilst acknowledging the dynamic nature of social media interactions. As Zhang and Centola (2019) argue, the combination of primary and secondary data in social media research provides crucial insights. However, this approach requires careful consideration of potential sampling biases and data quality issues inherent in social media research (Boyd and Crawford, 2012).

4.3.2 Collection Procedures and Timeline

The data collection process follows a sequential design, structured in two distinct phases. This sequential approach allows findings from the qualitative phase to inform and enhance the subsequent quantitative data collection, ensuring comprehensive coverage of emerging themes and patterns (Teddlie and Tashakkori, 2019). Whilst this approach extends the overall research timeline, it strengthens the validity of the findings through the iterative development of research instruments.

The first phase, focusing on qualitative data collection, was conducted between October and December 2023. During this phase, social media comments on health information dissemination were systematically extracted from major platforms, including WeChat, Douyin, and Weibo. The extracted comments were originally posted within 12 months, from 1st January 2023 to 31st December 2023. This timeframe was chosen to capture a full year's cycle of health information discussions, considering potential seasonal variations in health topics and user engagement patterns. Following Kozinets's (2020) guidelines for digital ethnography, the extraction process spanned twelve weeks, ensuring the collection of a comprehensive dataset that captures seasonal fluctuations in health-related discussions and user interactions.

Concurrent with comment extraction, twelve semi-structured interviews were conducted with selected participants. Each interview session lasted between 45 and 90 minutes, allowing for an in-depth exploration of participants' experiences with health information on social media. All interviews were recorded with participant consent and transcribed within 48 hours to ensure accurate capture of refinements and context. This rapid turnaround in transcription helps maintain data integrity and allows for preliminary analysis to inform subsequent interviews (Silverman, 2020). The interview phase concluded with a preliminary analysis that informed the development of the quantitative instrument.

The second phase, implemented between January and March 2024, focused on quantitative data collection through online survey questionnaires. This three-month period was strategically chosen not to avoid major holidays and to ensure optimal response rates. The survey remained active for eight weeks, with weekly monitoring of response patterns and data quality. This timeline allowed for sufficient data collection whilst maintaining the currency of the research within the rapidly evolving social media environment.

4.3.3 Quality Control Procedures

Quality control procedures were implemented throughout the data collection process to ensure data integrity. For qualitative data collection, interview procedures were standardised with detailed protocols for conducting and recording interviews. The social media comment extraction process followed systematic procedures to ensure comprehensive capture of relevant discussions.

For quantitative data collection, real-time monitoring systems were established to track response patterns and identify potential technical issues. This included monitoring of survey completion times and response rates to ensure data quality during the collection phase. Regular checks were conducted to identify and address any technical or procedural issues that might affect data collection.

Data security and ethical considerations were prioritised throughout the collection process. All collected data was encrypted and stored securely following industry standards (Townsend and Wallace, 2016), with particular attention to protecting sensitive health-related information and maintaining participant anonymity.

4.4 Sampling Strategy

Sampling is a crucial element in research design, directly affecting the representativeness of research results and the validity of inferences. This study adopts a multi-stage sampling strategy covering both qualitative and quantitative research to ensure sample representativeness and data reliability (Bryman, 2016).

4.4.1 Sampling Techniques

The study employed multiple sampling techniques across different research phases, carefully selected to address the specific requirements of each stage while ensuring comprehensive coverage of the research objectives.

Semi-structured Interviews

For the qualitative phase, semi-structured interviews employed a combination of purposive and snowball sampling techniques, with selection criteria directly aligned with the theoretical sampling approach outlined in 4.2.1.1. The initial purposive sampling identified key informants through professional networks and academic databases, focusing on individuals directly involved in health information dissemination or evaluation. This approach aligns with Mason's (2010) emphasis on selecting participants based on their potential to provide detailed insights into the phenomenon under study.

Building upon the selection criteria introduced in 4.2.1.1, participants were systematically recruited to ensure representation across four key stakeholder categories. The initial sample included healthcare professionals (one doctor and one nurse), media practitioners (one news editor and one social media influencer), academic professionals (one researcher and one educator/professor), and members of the general public with diverse occupational backgrounds (one salesman, one university student, one civil servant, one retiree, one fitness coach, and one housewife).

The sampling process progressed from initial purposive selection to subsequent snowball sampling, where initial participants recommended others with relevant experiences but potentially different perspectives. This expansion maintained the theoretical focus whilst broadening the range of contexts and experiences captured. Throughout this process, theoretical saturation remained the guiding principle for determining sample adequacy, as described in 4.2.1.1. This systematic approach to sampling ensured comprehensive coverage of different perspectives on health information dissemination and consumption on social media platforms while maintaining methodological rigour in the determination of sample size.

Social Media Comment Extraction

For social media comment extraction, the study implemented purposive sampling with specific selection criteria. This approach drew upon Stieglitz et al.'s (2018) framework for social media analytics, ensuring comprehensive coverage across different health topics while maintaining data quality and relevance. The sampling process included major social media platforms, including WeChat, Douyin, and Weibo, selected based on their user demographics and engagement patterns. The extraction process focused on seven primary health categories: infectious diseases, non-communicable diseases, vaccines, diet and nutrition, drug and smoking, public health measures, and mental health as identified in 2.2.

Questionnaire Survey

The quantitative phase employed simple random sampling combined with snowball sampling techniques. This straightforward approach, as supported by Bhattacherjee (2012), proved effective for reaching a broad range of social media users while capturing universal patterns of health information adoption behaviour. This aligns with the study's scope outlined in 1.6, which emphasises identifying common factors that influence all social media users rather than focusing on demographic-specific differences. The questionnaire distribution followed a multi-channel approach, utilising both direct distribution through health-related social media accounts and indirect distribution through participant referrals.

4.4.2 Sampling Criteria

The establishment of comprehensive sampling criteria ensured participant suitability and data quality while maintaining sample representativeness across all research phases.

Semi-structured Interviews

For the qualitative interviews, participant selection focused on obtaining diverse perspectives from individuals with varying professional backgrounds and social media experiences. Following Mason's (2010) emphasis on sample diversity in qualitative research, twelve participants were carefully selected to represent different social roles and experiences with health information on social media platforms. As detailed in Table 4.1, the participants included healthcare professionals (one doctor and one nurse), media practitioners (one news editor and one social media influencer), academic professionals (one researcher and one educator/professor), and members of the general public with diverse occupational backgrounds (one salesman, one university student, one civil servant, one retiree, one fitness coach, and one housewife). This purposive selection ensured comprehensive coverage of different perspectives on health information dissemination and consumption on social media platforms. All participants were required to have regular social media engagement and experience with health-related content consumption or sharing. This diverse sampling approach aligns with Miles et al.'s (2013) recommendations for achieving multifaceted insights in qualitative research.

No.	Gender	Occupation	No.	Gender	Occupation
A	Male	Doctor	G	Male	Salesman
B	Female	Nurse	H	Female	University Student
C	Male	News Editor	I	Male	Civil Servant
D	Female	Social Media Influencer	J	Female	Retiree
E	Male	Researcher	K	Male	Fitness Coach
F	Female	Educator/Professor	L	Female	Housewife

Table 4.1: Selection of Interview Informants

Social Media Comment Extraction

The criteria for social media comment selection focused on content relevance, temporal aspects, and engagement metrics. Following Vartanian's (2011) guidelines for secondary data analysis, comments were required to demonstrate a direct relation to health information, substantial engagement with health topics, and clear expression of user perspectives. Temporal constraints limited selection to comments posted within twelve months of data collection, ensuring relevance to current health discussions, while automated or commercial content was excluded to maintain authenticity. These criteria were systematically applied across all seven health categories identified in the study.

Questionnaire Survey

For the quantitative survey phase, the study employed simple random sampling combined with snowball sampling through online social media platforms. Given that the research focuses on social media users and the questionnaire was distributed online, there were no geographical restrictions on participant recruitment, allowing for broad participation across different regions. The only screening criterion was that participants must have experience of reading, obtaining, or following health information through social media platforms. This criterion will be clearly stated at the beginning of the questionnaire, and those who had never engaged with health information on social media were instructed to terminate their participation. This straightforward online sampling approach aligns with the study's aim to understand universal factors influencing health information adoption behaviour among social media users while ensuring the collected data comes from participants with relevant experience. The online distribution method through social media platforms naturally matched the study's target population and maintained consistency with the study scope outlined in 1.6.

4.4.3 Sample Size Determination

Determining appropriate sample sizes is crucial in research design, as it directly influences the statistical power, reliability of analyses, and generalisability of findings. This study employed a systematic approach to sample size determination for qualitative and quantitative phases, ensuring methodological rigour while considering practical constraints.

Qualitative Research Phase

For the semi-structured interviews, this study recruited 12 participants. This decision was informed by purposive sampling principles and data saturation considerations.

Research by Guest et al. (2006) demonstrated that meta-themes typically emerge within the first six interviews, with theoretical saturation occurring around 12 interviews. Francis et al. (2010) further supported this approach, noting that for theory-driven interview studies, 10-13 interviews typically suffice for reaching theoretical saturation. The selection of 12 participants thus provides sufficient depth for understanding social media users' health information adoption behaviours whilst maintaining research feasibility.

Regarding social media comment extraction, this study employed purposive sampling guided by theoretical saturation principles (Morse, 2015). Rather than predetermined quantities, the sampling continued until theoretical saturation was achieved—the point at which additional data ceased to yield new theoretical insights (Charmaz, 2014). This approach resulted in approximately 500-1000 substantive comments being analysed, providing substantive insights for theoretical development whilst avoiding analytical redundancy.

Quantitative Research Phase

The quantitative phase comprised two distinct stages: a pilot study and the main survey, each with specific methodological requirements and sampling considerations.

For the pilot study, 120 participants were recruited. This sample size determination was guided by multiple methodological considerations: Firstly, this sample size satisfies the minimum requirements for conducting Exploratory Factor Analysis (EFA). Comrey and Lee (1992) propose that 100-200 participants provide a fair basis for factor analysis whilst warning against samples below 100 as potentially unstable. Secondly, this sample size enables a meaningful assessment of internal consistency and construct validity (DeVellis, 2016). Research has demonstrated that Cronbach's alpha coefficients stabilise in samples of 100-200 participants (Charter, 2003), suggesting that sample size would provide reliable preliminary reliability estimates.

For the main survey, 500 valid responses were collected. This sample size determination was guided by several sophisticated methodological considerations: Firstly, the complexity of the proposed structural equation model necessitated a robust sample size. Whilst various guidelines exist, the most conservative approach suggests a minimum ratio of 10:1 between sample size and free parameters (Bentler and Chou, 1987). With 42 observed variables in the model, this yields a minimum requirement of 420 participants. Secondly, considerations of statistical power significantly influenced the final sample size decision. MacCallum et al. (1996) demonstrate that for complex structural models, samples of 500 or more provide sufficient power ($\beta > .80$) for detecting small but meaningful effects (RMSEA < .05) whilst maintaining precise parameter estimates. This sample size also enables narrow confidence intervals for RMSEA (Root Mean Square Error of Approximation), enhancing the precision of model fit assessment. Thirdly, the sample size accounts for the complexity of the proposed moderation and mediation analyses. According to Fritz and MacKinnon (2007), for detecting medium-sized indirect effects using bias-corrected bootstrap methods, a minimum sample size of 462 is recommended for .80 power. The sample size of 500 exceeds this requirement, ensuring adequate power for examining both direct and indirect effects within the structural model. To account for potential data quality issues, invalid responses, and outliers, the actual data collection target was set at 600 questionnaires. This oversampling strategy aligns with best practices in structural equation modelling research (Brown, 2015), ensuring that the final cleaned dataset would meet the target of 500 valid responses.

4.5 Data Collection Instruments

This study employs an interview guide, a social media comment extraction plan, a survey questionnaire and vignette scenarios used during the interview. Each tool has undergone careful design and pre-testing to ensure its validity and reliability.

4.5.1 Interview Guide

The interview guide serves as the core tool for qualitative data collection in this study. Adopting the form of semi-structured in-depth interviews, it includes both preset questions and allows interviewees to express their views freely, ensuring the depth and breadth of data (Kvale, 1996). The design of the interview guide follows the ‘funnel method’ principle, divided into three phases, to gradually deepen the understanding of users’ (1) perception, (2) discrimination and (3) behavioural tendencies towards health information. This three-stage approach allows for a gradual transition from broad general questions to more specific and in-depth inquiries, helping to establish rapport and encourage interviewees to provide detailed answers.

The interview guide contains 26 open-ended questions structured in three phases, as shown in Table 4.2. Phase 1 focuses on basic perceptions of health information, exploring participants’ attention patterns, interests, and general engagement with health information on social media. This phase establishes the foundation for understanding users’ baseline interaction with health information. Phase 2 examines participants’ discrimination of health information, investigating their ability to discern accurate information, factors influencing their judgment, and their verification processes. This phase includes the vignettes evaluation, which will be discussed in detail in 4.5.4. Phase 3 investigates behavioural tendencies, examining participants’ willingness to adopt health information, their past experiences, and their views on responsibility and governance measures.

Interview Phase	Focus Areas	Questions and Purposes
Phase 1 Basic Perceptions of Health Information (Q1-9)	Health information attention and acquisition frequency	Examine attention to health information and frequency of engagement
	Types of health information of interest	Identify types of health information of greatest interest
	Main purpose for seeking health information	Understand purposes for seeking health information
	Social media health information usage experience	Investigate social media health information experience
	Primary social media platforms used	Determine primary social media platforms used
	Active information seeking contexts	Explore contexts triggering active information seeking
	Information acquisition expectations	Understand expected outcomes from information acquisition
	Information reception attitudes	Investigate attitudes towards official/peer-shared information
	Self-assessment of health knowledge	Assess impact of health literacy on information attitudes
Phase 2 Discrimination of Health Information (Q10-16)	Ability to judge information accuracy	Assess ability to judge health information accuracy
	Judgment influencing factors	Explore factors influencing judgment
	Practical case evaluation	Evaluate actual health-related video content
	Information verification methods	Understand information verification methods
	Information source characteristic evaluation	Investigate source credibility assessment criteria
	Platform difference awareness	Examine impact of platform differences
	Contradictory information handling	Explore handling of contradictory information
Phase 3 Behavioural Tendencies (Q17-26)	Information adoption willingness	Explore willingness to adopt health information
	Adoption experience impact	Understand impact of positive adoption experiences
	Behavioural implementation	Investigate implementation of behavioural recommendations
	Implementation barrier analysis	Analyse implementation barriers and their impact
	Emergency situation response	Examine information use in emergency situations
	Information interaction behaviour	Understand information interaction behaviours and motivations
	Others' influence assessment	Assess influence of others' feedback
	Responsibility attribution	Explore attribution of accuracy responsibility
	Improvement suggestions	Gather suggestions for improvement measures
	Personal responsibility awareness	Understand perception of personal responsibility

Table 4.2: Structure and Content of Interview Guide

The development of the interview guide underwent a rigorous process to ensure its effectiveness and alignment with research objectives (Braun and Clarke, 2013). The guide underwent pre-testing with three individuals selected to represent different demographics and levels of social media engagement. This testing phase followed established qualitative research practices (Silverman, 2016), where participants were encouraged to think aloud whilst answering questions and provide feedback on clarity and relevance. Based on participant feedback, the wording of several questions was simplified to improve clarity. The order of questions was adjusted to facilitate a more natural flow of discussion. Additionally, specific probes were added to elicit more detailed responses. These improvements enhanced the guide's effectiveness in capturing relevant data.

The researcher implements the guide flexibly, following semi-structured interview best practices (Bryman, 2016). Rather than mechanically applying preset questions, the researcher adjusts the order according to the natural flow of conversation while maintaining focus on research objectives. The use of 'prompts or probes' is particularly important in encouraging detailed responses and exploring emerging themes (King and Horrocks, 2010). These techniques include requesting specific examples (Could you give me an example of that?), seeking clarification (What do you mean by...?), exploring feelings (How did that make you feel?), hypothesising scenarios (What would you do if...?), and drawing comparisons (How does this compare to...?).

As shown in Table 4.3, whilst the interview questions primarily address the first research objective of exploring influence factors, they also provide crucial data for the other three objectives. This comprehensive coverage is achieved through carefully designed questions that simultaneously capture information about theoretical constructs, adoption pathways, and governance implications.

Research Objective	Interview Questions	Purpose
Primary Objective 1: To explore factors influencing the adoption of health-related information on social media	Q1-3, Q8, Q13-15	To understand fundamental factors affecting information adoption through questions about attention patterns, trust in sources, and evaluation criteria
Secondary Objective 2: To construct a theoretical framework of factors influencing the adoption of health-related information on social media	Q4-7, Q12, Q16-18	To identify key variables and relationships through questions about usage patterns, practical evaluation, and adoption experiences
Secondary Objective 3: To examine the perception pathways of social media users in the process of adopting health-related information	Q9-11, Q19-23	To map the complete adoption journey through questions about knowledge levels, judgment processes, and behavioural outcomes
Secondary Objective 4: To propose governance and strategies recommendations for the management of health-related misinformation on social media	Q24-26	To gather user perspectives on governance through questions about responsibility attribution and improvement suggestions

Table 4.3: Alignment of Interview Questions with Research Objectives

The interview process strictly follows ethical operating guidelines. All participants are required to sign an Information Sheet and Consent Form before participating to ensure they fully understand the research purpose and their own rights. The researcher implements robust data protection measures, including anonymisation protocols and secure data storage systems, to ensure participant confidentiality. The complete interview guide, Information Sheet, and Consent Form are provided in Appendix I.

4.5.2 Social Media Comment Extraction

The extraction of social media comments serves as a vital source of naturalistic data in this study, offering insights into users' authentic responses to and engagement with health-related information. This method aligns with the growing recognition of social media platforms as rich sources of user-generated content for health communication research (Robillard et al., 2020). The analysis of social media comments provides unique advantages in understanding how users process, respond to, and share health information in their natural online environment (Taylor and Pagliari, 2018).

A systematic approach was implemented for the extraction process to ensure comprehensive and representative data collection. The selection of platforms included three major Chinese social media channels. WeChat official accounts often publish in-depth health articles, attracting detailed user comments and discussions, with the platform's emphasis on longer-form content providing context-rich user responses. Douyin, China's leading short-video platform, represents a crucial source of health-related content, with its comment system allowing immediate user feedback on health-related videos. Weibo, a microblogging platform, serves as a primary channel for health information dissemination in China, featuring verified accounts of healthcare institutions and professionals, with its threaded comment structure enabling the observation of extended discussions. These platforms were chosen based on their substantial user base and extensive health information dissemination patterns discussed in 2.2.

The health-related topics were systematically categorised into seven domains based on the 2.3. Information related to infectious diseases includes COVID-19, seasonal influenza, emerging infectious diseases, and prevention measures. Non-communicable diseases coverage includes cardiovascular diseases, diabetes, cancer, and chronic respiratory diseases. Vaccine-related information focuses on vaccination schedules, vaccine safety, new vaccine developments, and immunisation programmes. Diet and nutrition information covers dietary guidelines, food safety, nutritional supplements, and special dietary requirements. Drug and smoking-related information addresses substance abuse, smoking cessation, addiction treatment, and harm reduction strategies. Public health measures include environmental health, occupational health, health screening programmes, and emergency preparedness. Mental health information includes stress management, depression and anxiety, mental wellness, and professional support resources.

Regarding relevance, comments must demonstrate a direct discussion of health information or health-related topics, a clear connection to the original health content, engagement with specific health claims or recommendations, and discussion of personal health decisions or behaviours. In terms of substantiveness, priority was given to comments expressing personal viewpoints or experiences, detailed reasoning or argumentation, description of health information processing, sharing of health-related decision-making processes, integration of multiple information sources, and critical evaluation of health claims (Chen et al., 2020).

The temporal context was maintained by limiting comments to those posted within twelve months of data collection, considering seasonal health topics, relevance to current health trends and issues, and alignment with contemporary health discussions. Engagement metrics were assessed through the number of likes/upvotes, frequency of shares/reposts, quality of subsequent discussions, and impact on community discourse (Park et al., 2016).

The decision to employ manual extraction rather than automated web crawling was grounded in several methodological and ethical considerations. Manual extraction enables data quality control through the ability to interpret subtle meanings and contexts, recognise cultural and linguistic subtleties, identify irony and implied meanings, assess comment authenticity, and understand platform-specific communication patterns (Moorhead et al., 2013). Ethical considerations include compliance with platform terms of service, protection of user privacy, and adherence to research ethics guidelines (Association of Internet Researchers, 2019).

The advantages of this methodological approach include access to authentic, unfiltered user responses, contextual information, high relevance to research questions, quality control over data collection, ethical compliance, flexibility in data selection, and a deep understanding of user interactions. However, certain limitations must be acknowledged, including the potential for researcher bias in selection, limited sample size compared to automated methods, missing context in anonymous comments, variable quality of user-generated content, and challenges in maintaining consistent selection criteria (Lomborg, 2017).

4.5.3 Survey Questionnaire Design and Implementation

The survey questionnaire serves as the primary instrument for quantitative data collection in this research. It is designed to systematically gather comprehensive data on health information adoption behaviours among social media users. The questionnaire development process includes three distinct phases: initial design, pilot testing, and finalisation, with each phase carefully structured to ensure maximum validity and reliability of the research instrument.

Initial Questionnaire Development Process

The development of the initial questionnaire followed a rigorous process grounded in both theoretical foundations and empirical evidence. This process began with a comprehensive review of existing validated scales and incorporated findings from the preliminary qualitative research phase, ensuring both content validity and contextual relevance to the social media environment (DeVellis, 2016). The questionnaire structure was thoughtfully designed to facilitate clear understanding and accurate responses from participants while minimising potential biases and response fatigue.

The questionnaire consists of two parts. The first part collects basic demographic information, including participants' gender, age range, education level, whether participants have medical-related background knowledge, and their engagement patterns with health information on social media. While this demographic data helps describe the sample characteristics and verify the broad representation of different social media user groups, it is not intended for subgroup analysis, maintaining consistency with the study's focus on universal factors affecting health information adoption. The second part of the questionnaire comprises the measurement scales for the theoretical constructs identified through the qualitative research and literatures. This study employs a 7-point Likert scale for all measurement items, ranging from 'strongly disagree' (1) to 'strongly agree' (7).

Scale Design Rationale

The decision to employ a 7-point Likert scale, rather than the more commonly used 5-point scale, because research has demonstrated that 7-point scales provide enhanced sensitivity and discrimination in data collection, particularly when measuring complex psychological constructs such as attitudes and behavioural intentions (Preston and Colman, 2000). This increased granularity allows participants to express their attitudes with greater precision, which is especially important when investigating subtle aspects of health information adoption behaviour.

Additionally, the 7-point scale has been shown to reduce central tendency bias, as it provides more options for participants to reflect their true opinions accurately (Cox, 1980). This is particularly valuable in the context of health information research, where participants might otherwise default to neutral responses when faced with complex or ambiguous situations. The expanded range of options also helps to generate data properties that more closely approximate continuous data, making the results more suitable for sophisticated statistical analyses (Norman, 2010).

Pilot Study Implementation

Following the initial questionnaire development, a comprehensive pilot study involving 120 participants was conducted to assess and refine the instrument. The pilot testing phase was crucial for evaluating the questionnaire's effectiveness and identifying any potential issues before the main data collection phase. During this phase, both quantitative and qualitative feedback was collected from participants regarding the clarity of instructions, comprehensibility of items, and overall questionnaire structure.

The pilot study also served to validate the effectiveness of the questionnaire distribution method and to estimate the time required for completion. This information was valuable for refining the questionnaire administration process and ensuring that the final survey would be both efficient and effective. Based on the pilot study results, necessary adjustments were made to improve the clarity of instructions, refine question-wording, and optimise the overall questionnaire structure.

The pilot study data underwent rigorous statistical analysis, including reliability testing through Cronbach's alpha calculations and exploratory factor analysis (EFA) to verify the construct validity of the measurement scales. The results of these analyses were used to identify any problematic items or structural issues that needed to be addressed in the final version of the questionnaire (Field, 2013).

Final Questionnaire Implementation Strategy

The questionnaire was distributed across multiple social media platforms, including WeChat, Douyin, and Weibo, to capture a diverse range of user segments and minimise platform-specific biases. This multi-platform approach was particularly important given the research's focus on social media health information adoption behaviours.

Sample size determination for the main study was guided by both theoretical and practical considerations. The target sample size of 500 participants was established based on the requirements for structural equation modelling analysis, considering the complexity of the proposed theoretical model and the need for robust statistical testing. This sample size strikes a balance between ensuring adequate statistical power for hypothesis testing and avoiding the potential inflation of fit indices that can occur with excessively large samples (Kline, 2015; Schumacker and Lomax, 2016).

Quality control measures were implemented throughout the data collection process to ensure the integrity and reliability of the gathered data. These measures included careful screening of participants to ensure they met the inclusion criteria, such as being at least 18 years of age and having experience with health information on social media. The questionnaire distribution process was monitored continuously to maintain data quality standards throughout the collection period.

Throughout the implementation phase, particular attention was paid to maintaining ethical standards and protecting participant privacy. All participants were provided with clear information about the study's purpose and their rights as research subjects. The data collection process adhered to strict confidentiality protocols, with all responses being anonymised and stored securely.

4.5.4 Use of Vignette Scenarios

The use of vignettes in this research is an innovative approach to examining how social media users evaluate and respond to health-related information. Vignettes provide carefully constructed scenarios that simulate real-world encounters with health information on social media platforms.

Theoretical Foundation of Vignette Usage

The application of vignettes in this study is underpinned by robust methodological theory from social science research. Vignettes serve as carefully crafted hypothetical scenarios that enable systematic investigation of decision-making processes and evaluative judgments (Finch, 1987). This methodological approach is particularly valuable in health information research for three key reasons.

Firstly, vignettes overcome the limitations of direct questioning by providing standardised stimuli across participants, allowing for comparative analysis of how different individuals process identical health information scenarios (Hughes and Huby, 2004). This standardisation is crucial when studying the variable and often tacit processes through which individuals evaluate health information credibility.

Secondly, vignettes create a psychological distance that facilitates more candid discussion of potentially sensitive health information behaviours. As noted by Barter and Renold (1999), participants often feel more comfortable discussing their evaluative processes when responding to hypothetical scenarios rather than recounting personal experiences, which may be subject to social desirability bias or post-hoc rationalisation.

Thirdly, vignettes enable systematic manipulation of specific scenario elements while maintaining contextual realism. This controlled variation allows for identification of how contextual factors influence information evaluation processes—a critical consideration in health misinformation research where context significantly affects information credibility judgments (Jenkins et al., 2010).

The theoretical grounding of vignette methodology in constructivist research traditions aligns with this study's social constructivist stance. From this perspective, vignettes serve not simply as stimuli but as social texts that participants actively interpret and respond to, revealing their constructed understanding of health information contexts (Wilson and While, 1998). This theoretical alignment enhances methodological coherence while providing insights into the socially constructed nature of health information evaluation.

Development and Selection of Vignette Scenarios

The vignette scenarios used in this study were developed through a systematic, criteria-driven process to ensure their effectiveness as research instruments. This methodical approach ensured the selected scenarios would effectively stimulate discussion about information evaluation processes whilst maintaining relevance to participants' experiences.

The development process began with the identification of health topics that were both prevalent on Chinese social media platforms and represented different types of health information challenges. An initial content analysis of trending health topics on WeChat, Douyin, and Weibo during the three months preceding the study revealed recurring themes across infectious diseases, non-communicable diseases, nutrition advice, and preventive health measures. These observations were supplemented by consultations with two healthcare professionals who provided insights into common patterns of health misinformation circulating on social media platforms.

From this preliminary analysis, three distinct scenarios were selected to represent different temporal contexts and types of health information typically encountered on social media platforms:

The first vignette addresses the COVID-19 pandemic, representing a historical context that participants have just directly experienced. This scenario explores how users evaluated and responded to rapidly evolving health information during a global public health crisis.

The second vignette examines contemporary health claims about cola drinks and cancer risks. On 14th July 2023, the World Health Organization (WHO) announced that the International Agency for Research on Cancer (IARC) classified aspartame as 'possibly carcinogenic to humans' (WHO, 2023b). This topic remained highly discussed on social media platforms during the interview period in October and December 2023, making it an appropriate contemporary case for examining how users evaluate health information.

The third vignette explores chronic disease management, particularly focusing on diabetes and related lifestyle modifications. This forward-looking scenario examines how users engage with preventive health information and long-term health management strategies on social media platforms. The vignette incorporates elements of dietary advice, weight management recommendations, and lifestyle modification suggestions.

Selection Criteria and Evaluation

To ensure the methodological rigour of the vignette scenarios, each was systematically evaluated against four key criteria: topicality, rationality, universality, and controversy.

As shown in Table 4.4, these criteria provided a structured framework for assessing the suitability of each scenario for exploring health information evaluation processes.

Selection Criteria	Global Public Health Crisis (COVID-19)	Health Risk Claims (Cola and Cancer)	Chronic Disease Management (Diabetes)
Topicality	High relevance due to recent global impact and ongoing public health concerns	Current and persistent debate in public health discourse	Growing significance with increasing prevalence of lifestyle diseases
Rationality	Based on documented medical evidence and public health data	Builds on existing research about beverage consumption and health impacts	Supported by established medical guidelines and clinical evidence
Universality	Affects all demographic groups regardless of age, gender, or background	Relevant to most consumers due to widespread cola consumption	Applicable to growing population segment with interest in health management
Controversy	Debates over prevention measures, treatment approaches, and information sources	Conflicting claims between industry research and public health studies	Competing approaches to disease management and lifestyle interventions

Table 4.4: Vignettes Selection Criteria and Scenario Analysis

The topicality criterion ensured scenarios addressed health issues with contemporary relevance, maximising participant engagement and reflecting actual content encountered on social media platforms. The rationality criterion assessed whether scenarios presented plausible situations based on established medical information, avoiding scenarios so implausible that participants would dismiss them outright. The universality criterion ensured scenarios would be broadly relevant across demographic groups, important for capturing diverse perspectives. Finally, the controversy criterion assessed whether scenarios contained sufficient ambiguity or conflicting viewpoints to necessitate active evaluation, stimulating articulation of decision-making processes.

Implementation in Research Process

The implementation of vignettes in the interview process followed a standardised protocol to ensure methodological consistency while enabling in-depth exploration of participants’ evaluation processes. All twelve interview participants were presented with all three vignette scenarios in the same sequence, moving from the COVID-19 scenario to the cola/cancer scenario and finally to the diabetes management scenario. This consistent presentation enabled systematic comparison across participants while controlling for potential order effects.

Each vignette presentation followed a structured three-phase protocol. In the presentation phase, the scenario was read verbatim to participants from a prepared script, ensuring consistent stimulus presentation. The vignette text was then provided to participants in written form for reference during discussion. In the response phase, participants were asked a standard set of questions exploring how they would evaluate the presented information, what factors would influence their trust or scepticism, and whether they would share or act upon the information. In the exploration phase, follow-up probing questions were employed to investigate participants’ reasoning processes and the specific informational cues they used to evaluate credibility.

This implementation approach was specifically designed to capture both initial reactions and deeper reflection, allowing participants to articulate their evaluation processes in increasing detail. The standardised questioning protocol ensured comparability across participants, while the flexible probing approach enabled exploration of individual differences in information processing strategies.

The vignettes were integrated within the second phase of the interview structure, as outlined in Table 4.2, positioned after general questions about health information experiences but before detailed questions about sharing behaviours. This strategic placement allowed participants to first establish comfort discussing health information in general terms before engaging with specific scenarios, while ensuring the vignette discussions could inform subsequent questions about information sharing and adoption behaviours.

This systematic implementation approach generated data on participants' information evaluation strategies across different health contexts, revealing both consistent patterns and context-dependent variations in health information adoption decisions. The consistent presentation and questioning process also facilitated cross-case comparison during the subsequent analytical phase, enabling robust identification of common evaluation factors while acknowledging contextual influences.

4.6 Data Analysis

This study employs both qualitative and quantitative analytical approaches in accordance with the exploratory sequential mixed methods design. The qualitative analysis aims to explore and understand key factors influencing health information adoption on social media through systematic analysis of interview data and social media comments. The quantitative analysis subsequently tests the theoretical model and hypotheses derived from the qualitative findings through statistical methods.

4.6.1 Qualitative Data Analysis

The qualitative analysis phase adopts a grounded theory approach to systematically examine interview transcripts and social media comments. This approach enables the identification of key factors and patterns in how social media users evaluate and adopt health-related information. The analysis process consists of three main components: data preparation and translation, grounded theory analytical process, and integration of findings from different data sources.

4.6.1.1 Data Preparation and Translation

The cross-language nature of this research necessitates careful attention to data preparation and translation processes to ensure research quality. In cross-language qualitative research, maintaining the authenticity and richness of participants' expressions while accurately conveying their meaning in another language presents significant challenges (van Nes et al., 2010). This study primarily deals with two types of qualitative data: semi-structured interview transcripts and social media comments, both originally in Chinese.

For interview data, all conversations were first transcribed verbatim in Chinese. This process involved converting audio recordings into text while preserving significant non-verbal elements, such as pauses and tonal changes that might affect interpretation. This approach aligns with Bailey's (2008) emphasis on capturing both verbal and non-verbal aspects in qualitative data transcription to maintain the full context of communication. Each transcript was reviewed multiple times against the original recording to ensure accuracy. To protect participant confidentiality, each interviewee was assigned an anonymous identifier (e.g., P1, P2, etc.), following established ethical guidelines in qualitative research (Gibbs, 2007).

Social media comments were manually collected from designated platforms (WeChat, Douyin, and Weibo). Each comment was documented in its original form in an Excel spreadsheet, excluding any personally identifiable information. This approach to social media data collection aligns with Kozinets's (2015) guidelines for ethical ethnographic research.

To assist with translation accuracy and consistency, DeepL was employed as a tool, and content was manually reviewed and refined to ensure conceptual equivalence and contextual appropriateness. Given that the researcher's native language is Chinese, the initial analysis was conducted in Chinese to preserve the subtle understanding of participants' expressions, as recommended by Temple and Young (2004) for maintaining conceptual accuracy in cross-language research. When encountering culturally specific terms or expressions without direct English equivalents, explanatory notes were added to provide necessary context and clarification. This approach aligns with Chen and Boore's (2010) recommendations for maintaining conceptual equivalence in cross-language qualitative research. The translation process particularly focused on preserving the cultural and contextual meanings of health-related terms and expressions, following Squires's (2009) guidelines for maintaining cultural competence in cross-language research.

4.6.1.2 Ground Theory Analytical Process

The study employs a grounded theory approach using Excel for data management and analysis. This methodology, initially developed by Glaser and Strauss (1967) and further refined by Charmaz (2006), provides a rigorous framework for analysing qualitative data and developing theoretical understanding. The analytical process follows three distinct coding stages, as outlined by Corbin and Strauss (2015): open coding, axial coding, and selective coding. Each stage progressively builds upon the previous one to develop an increasingly refined theoretical understanding of health information adoption behaviours on social media.

Open Coding

In the open coding stage, the researcher conducted a detailed examination of both interview transcripts and social media comments. Following Holton's (2010) guidance on initial coding practices, each segment of data was carefully analysed to identify key concepts. For the interview data, this involved line-by-line analysis of participants' descriptions of their experiences with health information on social media. Each statement or idea was assigned an initial code that closely reflected the participant's language and meaning. For social media comments, a similar detailed coding process was applied, with each comment being analysed for underlying meanings and patterns.

Axial Coding

The axial coding stage focused on establishing connections between the initial codes identified during open coding. As described by Goulding (2002), this stage involves reassembling data that was fractured during open coding to form more comprehensive categories. For interview data, the researcher clusters similar concepts and explores the relationships between them. The researcher pays particular attention to causal relationships, conditions, and contextual factors described by participants (Corbin and Strauss, 2015). For social media comment data, the researcher similarly combines related initial codes into broader themes. In this process, the researcher constantly compares different concepts and categories, seeking connections and differences between them.

Selective Coding

Selective coding is the final stage, aiming to integrate the analysis results from previous stages and determine core categories (Corbin and Strauss, 2015). At this stage, the researcher attempts to construct a comprehensive explanatory and relationship framework. For interview data, the researcher determines a core category through repeated comparison and analysis. Then, the researcher links other major categories to this core category, forming a coherent theoretical model. For social media comment data, the researcher similarly seeks a core concept that can integrate all major themes. In this process, the researcher constantly returns to the original data, verifying whether the newly formed theory can explain most of the data variation. If certain aspects are found to be insufficiently explained, the researcher revisits the data, adjusting categories and relationships until theoretical saturation is achieved.

4.6.1.3 Triangulation and Integration of Qualitative Findings

The integration of findings from different data sources follows Denzin's (2012) principles of methodological triangulation, which emphasises the importance of using multiple data sources to develop a more comprehensive understanding of complex phenomena. As suggested by Patton (2015), this triangulation process helps enhance the credibility and depth of qualitative findings by comparing insights from different perspectives.

Following Flick's (2018) guidelines for systematic triangulation, the integration process involved several steps: Firstly, themes and patterns identified from interview data were systematically compared with those emerging from social media comments. This comparison followed Eisenhardt's (1989) recommendations for cross-case analysis, looking for both similarities and differences in how health information adoption manifests in different contexts. Secondly, the researcher examined how findings from different sources complemented or contradicted each other. For example, while interview participants often provided rational, considered explanations for their information evaluation processes, social media comments frequently revealed more immediate, emotional responses to health information. This aligns with Bazeley's (2013) observations about the value of comparing different types of qualitative data to understand both explicit and implicit aspects of social phenomena. Finally, following Yin's (2016) approach to qualitative synthesis, the findings were integrated into a comprehensive framework. This integration process revealed important insights about how users' stated preferences for health information evaluation sometimes differed from their actual behaviour in social media environments.

4.6.2 Quantitative Data Analysis

The quantitative data analysis phase serves to empirically test the key factors and hypotheses refined through the qualitative research stage. This study implements a comprehensive statistical analysis framework to examine the questionnaire data systematically. The analysis includes descriptive statistics, scale reliability and validity assessments, Exploratory Factor Analysis (EFA), Confirmatory Factor Analysis (CFA), Structural Equation Modelling (SEM), and path analysis.

Prior to formal analysis, preliminary data preparation and cleaning procedures are undertaken. This involves systematic data coding, thorough checking for completeness, and appropriate handling of missing values and outliers (Hair et al., 2018). Invalid responses are identified and removed based on established criteria, including unusually brief completion times and uniform response patterns (Krosnick and Presser, 2010).

4.6.2.1 Descriptive Statistics

The descriptive statistical analysis serves as the foundation for understanding the dataset's characteristics. This phase involves computing and analysing frequency distributions, means, and standard deviations for demographic variables, including gender, age, educational attainment, medical knowledge background, and social media health information consumption patterns (Field, 2018).

The analysis also includes normality testing to verify the underlying distributional assumptions. Following established guidelines, the study employs skewness and kurtosis statistics to assess normality (George and Mallery, 2019). In accordance with Kline's (2011) criteria, data are considered approximately normal when skewness values fall within ±3 and kurtosis values within ±8.

4.6.2.2 Scale Reliability and Validity

Reliability Analysis

The study implements a rigorous reliability assessment framework across both the pilot and main survey phases. This comprehensive approach utilises Cronbach's alpha coefficient, Composite Reliability (CR), and Average Variance Extracted (AVE) to evaluate internal consistency and convergent validity (Hair et al., 2018).

The rationale for conducting reliability analyses in both the pre-survey and main survey is because of several methodological considerations. Firstly, the pre-survey has a limited sample size may not fully capture population characteristics, whereas the main survey has a larger sample providing more robust reliability estimates (DeVellis, 2016). Secondly, repeated reliability testing enables the assessment of measurement stability across different samples, contributing to scale validation (Pallant, 2020). Additionally, reliability analysis serves as a prerequisite for subsequent CFA and SEM analyses, ensuring measurement quality meets established standards (Brown, 2015).

The study employs three primary reliability indicators: Cronbach's alpha coefficient assesses inter-item consistency, with values exceeding 0.70 indicating acceptable reliability (Nunnally and Bernstein, 1994). Composite Reliability (CR) evaluates construct-level reliability, offering a more stringent assessment than Cronbach's alpha (Hair et al., 2018). CR values above 0.70 indicate good reliability, while values between 0.60 and 0.70 may be acceptable if other validity indicators are good. Average Variance Extracted (AVE) quantifies the variance captured by constructs relative to measurement error, with values above 0.50 suggesting adequate convergent validity (Fornell and Larcker, 1981).

Validity Analysis

Validity assessment includes both content and construct validity dimensions (Hair et al., 2018). Content validity was established through the integration of existing validated scales from previous studies with qualitative research findings from interviews and social media comment analysis. The measurement items were adapted to fit the specific context of health information dissemination on social media. Construct validity examination incorporates both convergent and discriminant validity analyses through sequential EFA and CFA approaches.

The EFA phase, conducted during the pilot study, employs Kaiser-Meyer-Olkin (KMO) sampling adequacy testing and Bartlett's sphericity test to verify data suitability for factor analysis. KMO values above 0.80 indicate meritorious sampling adequacy, while significant Bartlett's test results ($p < 0.05$) confirm sufficient inter-item correlations (Tabachnick and Fidell, 2019). Principal component analysis with Varimax rotation extracts factors explaining maximum variance, with factor retention decisions based on multiple criteria, including eigenvalues > 1 and scree plot examination.

The CFA phase validates the theoretical measurement model using multiple fit indices. The chi-square statistic (χ^2) and its associated p-value are reported but not relied upon exclusively due to their sensitivity to sample size. Instead, the analysis emphasises practical fit indices, including the Root Mean Square Error of Approximation (RMSEA) with its 90% confidence interval, Normed Fit Index (NFI), Incremental Fit Index (IFI), Tucker-Lewis Index (TLI), and Comparative Fit Index (CFI) (Hu and Bentler, 1999). The acceptable model fit is indicated by RMSEA values below 0.08 (with its 90% confidence interval upper bound not exceeding 0.08) and NFI, IFI, TLI, and CFI values exceeding 0.90.

Convergent validity is assessed through examination of factor loadings (should exceed 0.50), AVE values (should exceed 0.50), and CR values (should exceed 0.70). Discriminant validity is evaluated by comparing the square root of AVE values with inter-construct correlations, where the square root of AVE values should exceed the inter-construct correlations for each construct (Hair et al., 2018).

4.6.2.3 Structural Equation Modelling

Structural Equation Modelling (SEM) represents an advanced multivariate analytical technique capable of simultaneously examining relationships amongst multiple latent and observed variables. This approach is particularly suitable for validating complex theoretical models with multiple interdependent relationships (Hair et al., 2018). The implementation of SEM in this study follows a systematic four-stage process.

The first stage involves the model specification, wherein the theoretical model is constructed based on qualitative findings and comprehensive literature synthesis. This stage includes defining measurement models for each latent construct and specifying structural relationships between constructs (Kline, 2015). The measurement model defines the relationship between observed variables and their underlying latent constructs, while the structural model specifies hypothesised causal relationships between latent variables. Particular attention is paid to ensuring theoretical justification for all specified relationships.

The second stage addresses model identification through a comprehensive assessment of identification conditions. Following established guidelines, each latent construct is measured by a minimum of three indicators to ensure stable parameter estimation (Brown, 2015). This requirement helps avoid identification problems and improves estimation stability. The model maintains recursive relationships without feedback loops, ensuring mathematical identification. Additionally, the scaling of latent variables is achieved through the marker variable approach, fixing one-factor loading per construct to unity (Byrne, 2016). Model identification is further verified by examining the degrees of freedom and ensuring the number of known parameters exceeds the number of free parameters to be estimated.

The third stage includes model estimation using Maximum Likelihood Estimation (MLE). This estimation method is selected for its robustness under conditions of multivariate normality and large sample sizes ($n > 200$). The choice of MLE is further supported by its ability to provide asymptotically unbiased, consistent, and efficient parameter estimates (Kline, 2015). Prior to estimation, data screening procedures are implemented to assess multivariate normality, identify outliers, and handle missing data appropriately. The estimation process involves iterative procedures to minimise the difference between the observed covariance matrix and the model-implied covariance matrix.

The fourth stage involves a comprehensive evaluation of the model using multiple complementary fit indices. The chi-square test, divided by the degrees of freedom (CMIN/*df*), provides an initial assessment of the overall model fit, with values below 3 indicating acceptable fit (Kline, 2015). The Root Mean Square Error of Approximation (RMSEA) offers an assessment of model parsimony, with values below 0.08 indicating acceptable fit and values below 0.06 suggesting good fit (Hu and Bentler, 1999). The Normed Fit Index (NFI), Incremental Fit Index (IFI), Tucker-Lewis Index (TLI), and Comparative Fit Index (CFI) provide comparative fit assessments, with values above 0.90 considered acceptable and above 0.95 indicating good fit (Hair et al., 2018;

Schumacker and Lomax, 2016). These fit indices will be used to evaluate the model's fit to the data and determine whether the proposed theoretical model adequately represents the observed relationships among the variables.

Model modification, if necessary, is approached with caution and guided by both theoretical considerations and empirical indicators. Modification indices are examined to identify potential model improvements, while standardised residuals help identify local areas of misfit. However, any model modifications are implemented only when theoretically justified and substantively meaningful, maintaining the balance between model fit and theoretical integrity (Hair et al., 2018).

4.6.2.4 Path Analysis

Path analysis in this study includes both mediation and moderation analyses, employing a sequential approach to examine complex variable relationships. This study adopts a step-by-step path analysis strategy, mainly based on the following considerations: Firstly, it allows for precise examination of distinct theoretical mechanisms, enabling clear differentiation between mediating processes and moderating conditions (Hayes, 2018a). Secondly, it maintains model parsimony whilst ensuring the interpretability of results, avoiding the complexity that might arise from simultaneous estimation of all effects (Little et al., 2007). Thirdly, it enables the application of specialised analytical techniques appropriate for each type of effect, maximising the accuracy and reliability of results (Preacher et al., 2017).

Mediation Effect Analysis

The mediation analysis employs a bootstrap-based approach implemented through AMOS, following contemporary best practices in testing indirect effects. The analysis proceeds through several systematic steps designed to provide a comprehensive examination of mediating relationships. Initial model specification involves establishing direct, indirect, and total effects within the mediation framework, ensuring clear delineation of hypothesised mediating pathways. The bootstrap procedure utilises

5,000 resamples with bias-corrected 95% confidence intervals, providing robust estimates of indirect effects (Hayes, 2018a). This approach offers advantages over traditional methods by not assuming the normality of the sampling distribution of indirect effects and providing more accurate confidence intervals.

The mediation analysis examines multiple aspects of mediating relationships. The significance of indirect effects is assessed through bootstrap confidence intervals, with intervals excluding zero indicating significant mediation. The size and direction of specific indirect effects are calculated to understand the magnitude and nature of mediating relationships. The proportion of mediation is examined through the ratio of indirect to total effects, providing insight into the relative importance of mediating pathways. The type of mediation (complete versus partial) is determined based on the significance of direct effects after accounting for indirect effects, offering insight into the nature of mediating processes (Zhao et al., 2010).

Moderation Effect Analysis

The moderation analysis employs SPSS Process Macro (Hayes, 2018b), which was selected for its ability to handle complex conditional process analysis. The implementation follows a structured approach designed to provide a comprehensive examination of moderating effects. Continuous variables are mean centred prior to analysis to reduce multicollinearity and facilitate the interpretation of interaction terms. The analysis proceeds with testing interaction terms using Model 1 for single moderators, examining the statistical significance and nature of moderating effects.

The examination of moderation effects includes several key components. Conditional effects are examined at different moderator levels, typically at one standard deviation below the mean, at the mean, and one standard deviation above the mean to understand how the relationship between predictor and outcome variables varies across different values of the moderator. This approach provides a structured way to interpret how the strength or direction of relationships changes under different conditions. Interaction effects are visualised through carefully constructed plots, facilitating the interpretation and communication of results. These plots illustrate the relationship between the predictor and outcome variables at different levels of the moderator, making complex interaction patterns more accessible and interpretable.

Simple slope analyses are conducted at meaningful moderator values, typically at one standard deviation above and below the mean for continuous moderators. This approach provides a detailed examination of the nature of moderation effects, revealing how relationships between variables change under different conditions (Aiken and West, 1991). Particular attention is paid to regions of significance, identifying the range of moderator values where effects are statistically significant and meaningful.

4.7 Data Validity and Reliability

Data validity and reliability are fundamental considerations in mixed-methods research, particularly when investigating complex phenomena such as health misinformation dissemination on social media. This study implements comprehensive measures to ensure methodological rigour across both qualitative and quantitative phases whilst maintaining coherence in the overall mixed-methods design.

4.7.1 Qualitative Research Validity and Reliability

The qualitative phase of this research employs several strategies to enhance the trustworthiness and credibility of findings. These strategies are implemented systematically throughout the data collection and analysis process to ensure robust qualitative research outcomes.

Credibility and Dependability

To ensure credibility, this study implements methodological triangulation through both interviews and social media comment analysis (Denzin and Lincoln, 2018). The interview process follows a standardised protocol developed based on established qualitative research principles. All interviews are conducted by the same researcher to minimise interviewer variance and ensure consistency in data collection. The protocol includes specific guidelines for interview conduct, probing techniques, and response recording, which enhances the dependability of the data collection process.

The analysis of social media comments provides naturally occurring data that complements and validates interview findings. This dual-source approach allows for cross-validation of emerging themes and ensures that findings are not artificially constrained by the interview context. The combination of directed interviews and naturalistic social media data provides a more comprehensive understanding of how users interact with and process health information on social media platforms.

Data Saturation and Sampling Adequacy

Data collection continues until theoretical saturation is achieved, following Morse's (2015) criterion that no new themes or theoretical insights emerge from additional data. The saturation point is determined through ongoing analysis during the data collection process, where each new interview or set of social media comments is analysed for novel concepts or themes. This iterative process ensures comprehensive coverage of the phenomenon under study whilst maintaining analytical rigour.

The sampling process is guided by purposive sampling principles, ensuring that participants are selected based on predefined criteria relevant to the research objectives while allowing for sample expansion through professional networks.

Researcher Reflexivity

The researcher maintains a reflective attitude during data collection and analysis, avoiding the influence of personal biases on data interpretation and ensuring the transparency and objectivity of data analysis (Mays and Pope, 2000). During the data analysis process each step of the data analysis process is recorded in detail, including detailed explanations of coding, category formation, and theory construction. Detailed recording helps ensure the transparency and repeatability of the data analysis process.

Other researchers can review and verify the research results through these records, thereby enhancing the credibility of the research (Lincoln and Guba, 1985). These detailed records also include verbatim transcription of interview records and detailed classification and annotation of social media comments, ensuring the accuracy and completeness of data analysis.

Personal Position Statement

The researcher acknowledges the importance of transparency regarding the researcher's position in relation to the research topic. The researcher's interest in health information dissemination on social media stems from both academic curiosity and personal concern about the potential impacts of misinformation on public health outcomes. As both a researcher and a social media user, the researcher approaches this study with the motivation to contribute to improving the quality of health information available on social media platforms, particularly in the Chinese context.

The researcher's dual identity as an academic investigator and a member of the social media user community being studied creates both advantages and challenges. This insider perspective provides valuable contextual understanding of Chinese social media ecosystems and cultural nuances that might influence health information adoption. However, this position may potentially introduce certain preconceptions about how users engage with health information.

Throughout the research process, several strategies were implemented to maintain analytical neutrality. During interviews, the researcher consciously avoided leading questions or expressions that might signal the researcher's own views on health information quality or sources. In analysing both interview data and social media comments, systematic coding procedures were employed alongside detailed analytical memos to monitor potential interpretive biases. When examining the various stakeholders involved in health information dissemination (users, content creators, platform providers, and health authorities), the researcher deliberately sought to understand and represent multiple perspectives without privileging any particular viewpoint.

The researcher recognises that complete neutrality is neither possible nor necessarily desirable in qualitative research; instead, transparency and reflexivity have been prioritised. Throughout the data collection and analysis process, assumptions and interpretations were continuously questioned, with alternative explanations sought for the patterns observed. By explicitly acknowledging this position and implementing these reflexive practices, the researcher aims to enhance the trustworthiness of the findings while allowing readers to form their own judgments about how the researcher's perspective may have shaped the research.

4.7.2 Quantitative Research Validity and Reliability

The quantitative phase implements robust statistical procedures to ensure measurement quality. These procedures follow established guidelines for scale development and validation while incorporating specific considerations for social media research contexts.

Data Preparation

Before formal analysis, the collected data is first organised and prepared. Data organisation includes coding and input to ensure the completeness and accuracy of the data (Hair et al., 2010). Additionally, invalid questionnaires, such as those with excessively short answer times or identical options for all questions (Krosnick, 1999), need to be removed. These steps help improve data quality and ensure the reliability of analysis results.

Scale Reliability

Internal consistency reliability is assessed through multiple complementary measures. Cronbach's alpha coefficients are calculated for each scale, with a minimum threshold of 0.70 established based on methodological literature (DeVellis, 2016). This analysis is supplemented by Composite Reliability (CR) measures, which provide a more robust assessment of internal consistency in the context of structural equation modelling. The CR threshold is similarly set at 0.70.

Construct Validity

Construct validity is established through a comprehensive validation process incorporating multiple forms of validity assessment. The measurement items were developed through the integration of existing validated scales from previous studies with qualitative research findings, with particular attention paid to their relevance in the social media health information context. This approach ensures the measures appropriately capture the theoretical constructs while maintaining contextual applicability.

The construct validation process begins with exploratory factor analysis (EFA) using a pilot sample. The EFA results inform initial construct boundaries and item assignments. This is followed by confirmatory factor analysis (CFA) using the main study sample, which verifies the factor structure and assesses model fit. The model fit indices include the comparative fit index (CFI) and Tucker-Lewis index (TLI), both with thresholds of 0.90 and root mean square error of approximation (RMSEA) with a threshold of 0.08.

Convergent and discriminant validity are assessed through multiple criteria. Average Variance Extracted (AVE) is calculated for each construct, with a minimum threshold of 0.50 established to demonstrate adequate convergent validity. Factor loadings are examined with a threshold of 0.70, ensuring that items are strongly related to their intended constructs. The Fornell-Larcker criterion is applied to assess discriminant validity, ensuring that constructs are sufficiently distinct from one another.

4.8 Ethical Considerations

This research adheres to rigorous ethical standards throughout its mixed-methods investigation of health misinformation on social media. The study was conducted in accordance with the ethical guidelines of the University of Wales Trinity Saint David and fundamental research ethics principles. The ethical framework for this study is grounded in three core principles: respect for persons, beneficence, and justice (Israel, 2014). These principles guided the implementation of ethical considerations across three critical phases: preparatory procedures, data collection and management, and analysis and dissemination.

Preparatory Procedures

The research commenced only after securing approval from the University's Research Ethics Committee through a comprehensive PG2 Ethics Form. This process involved detailed risk assessments addressing the potential vulnerabilities of participants when discussing health misinformation experiences, particularly concerning sensitive health topics. The assessment considered both direct risks to participants and broader societal implications of studying health misinformation (Iphofen, 2020). This preparatory phase established protocols for managing potential psychological distress, ensuring participant autonomy, and maintaining data security.

Data Collection and Management

Informed Consent formed the cornerstone of ethical data collection. Participants received information sheets detailing the study's purpose, methodology, and data usage (Christians, 2018). These documents emphasised voluntary participation, the right to withdraw, and confidentiality measures. For the qualitative phase, interview participants were offered choices in interview settings and timing to ensure comfort and minimise potential stress. The quantitative survey phase implemented strict anonymity protocols, which was particularly crucial given the sensitive nature of health information behaviour on social media.

The research employed specific safeguards for social media data collection, acknowledging the unique ethical challenges of digital environments (Markham and Buchanan, 2012). While social media comments were treated as public domain data, they were anonymised during extraction and analysis to protect user privacy. The study maintained a careful balance between research objectives and ethical obligations, particularly regarding the consent process for social media data usage.

Analysis and Dissemination

Data analysis adhered to principles of scientific integrity and participant protection (Hammersley and Traianou, 2012). All collected data underwent thorough anonymisation, with identifying information removed and replaced with coding systems. The storage of research data followed stringent security protocols, including encryption of digital files and secure storage of physical documents, with access restricted to authorised research personnel.

The reporting phase emphasised accurate representation of findings while maintaining participant confidentiality. The research design specifically addressed the ethical complexities of studying health misinformation. Care was taken to avoid inadvertently amplifying misleading health information during the research process. The interview protocol and questionnaire design incorporated safeguards to prevent potential harm to participants whilst maintaining research integrity (Iphofen, 2011). This included careful consideration of how to frame questions about health misinformation without reinforcing incorrect beliefs.

Throughout the analysis and reporting phases, this study maintained a commitment to research integrity through transparent documentation of methodological decisions and analytical processes. This transparency extends to acknowledging the limitations of the research and potential biases, reflecting the ethical obligation to present findings honestly and accurately (Tracy, 2020).

4.9 Chapter Summary

This chapter comprehensively introduces the mixed research methods employed in this study, which adopts an exploratory sequential design. In the qualitative phase, 12 interviewees are recruited through purposive and snowball sampling for semi-structured interviews incorporating vignette scenarios. In order to complement the interview data, social media comments are extracted from WeChat, Douyin, and Weibo using purposive sampling across seven predefined health categories. Both data use grounded theory analytical processes: open coding, axial coding, and selective coding. In the quantitative phase, a preliminary pilot study with 120 participants is conducted to assess the questionnaire's reliability and validity. Following necessary refinements based on the pilot results, the main survey collects 500 valid responses through social media channels using simple random and snowball sampling.

The chapter provides detailed explanations of data collection procedures, sampling strategies, research instruments, and analytical methods for both qualitative and quantitative phases. It also addresses crucial aspects of research quality assurance, including validity, reliability, and ethical considerations.

The next chapter will present the findings from the qualitative study. Through analysis of interview data and social media comments, key factors influencing health information adoption on social media are identified.

Chapter 5 Qualitative Findings

5.1 Overview

This chapter presents the qualitative research process and findings regarding factors influencing health information adoption on social media. The study employs a dual data collection strategy, combining semi-structured interviews and social media comment analysis. This approach not only allows for in-depth exploration of individual perspectives and experiences but also captures users' genuine reactions in natural environments, thereby providing richer and more reliable research data. This study first analysing interview transcripts from 12 participants, followed by analysing a large number of health-related social media comments. Both data sets use grounded theory analytical processes: open coding, axial coding, and selective coding. The research can understand influencing factors from different angles through independent analysis of interview data and social media comments. Finally, through triangulation and integrated analysis, research findings are further validated and consolidated.

5.2 Interview Study Findings

The study employed semi-structured interviews as the qualitative data collection method, engaging twelve participants in detailed discussions. The interviews, lasting between 45 and 90 minutes, were structured around three key domains: (1) perception, (2) discrimination, and (3) behavioural tendencies regarding health information on social media platforms. This approach facilitated the collection of subtle data that clarifies the complex dynamics of health information adoption (Braun and Clarke, 2006).

The participant selection process followed purposive sampling principles (Mason, 2002) with specific inclusion criteria: participants needed to be at least 18 years of age, have a minimum of three years of active social media usage, demonstrate regular engagement with social media platforms, and represent diverse occupational backgrounds.

The final participant cohort comprised twelve individuals representing diverse professional backgrounds, including healthcare practitioners, media professionals, educators, and various other occupations (see Table 5.1). This occupational diversity enabled the capture of multiple perspectives on health information adoption behaviours across different social contexts (Patton, 2015).

No.	Gender	Occupation	Interview Method	Duration
A	Male	Doctor	Face to face	90 minutes
B	Female	Nurse	Face to face	63 minutes
C	Male	News Editor	Face to face	50 minutes
D	Female	Social Media Influencer	Face to face	62 minutes
E	Male	Researcher	Online video call	66 minutes
F	Female	Educator/Professor	Face to face	90 minutes
G	Male	Salesman	Online voice call	45 minutes
H	Female	University Student	Online voice call	55 minutes
I	Male	Civil Servant	Online voice call	45 minutes
J	Female	Retiree	Online video call	45 minutes
K	Male	Fitness Coach	Online video call	65 minutes
L	Female	Housewife	Online voice call	45 minutes

Table 5.1: Profile of Interview Informants

The interviews were conducted through face-to-face meetings and online communication platforms. All sessions were audio recorded and subsequently transcribed verbatim for analysis. This mixed-mode approach to data collection enhanced accessibility while maintaining data quality (Creswell, 2014).

5.2.1 Data Analysis Process

The analysis followed a grounded theory approach, drawing primarily on the constructivist framework outlined by Charmaz (2014) and the analytical procedures described by Corbin and Strauss (2008).

5.2.1.1 Open Coding

The initial data analysis phase involved a rigorous line-by-line examination of interview transcripts, implementing the constant comparative method (Charmaz, 2014). Through an iterative process of data examination, conceptualisation, and categorisation, it generated 57 distinct conceptual codes (designated with the letter 'A' plus numbers, e.g., A1, A2, A3). The analysis included over 300 pages of coded transcripts from the 12 interviews.

Given the substantial volume of data, Table 5.2 presents one page of excerpt from the complete 300-page interview analysis documentation to demonstrate the systematic coding process through three distinct stages: (1) extraction of relevant quotes from interview transcripts, (2) conceptualisation of the underlying meanings and patterns, and (3) categorisation into preliminary conceptual groups.

Participant	访谈原文节选	Excerpts from the original interview transcripts	Conceptualisation	Categorisation
A	社交媒体上的通用建议可能并不适用于特定患者。	Generic advice on social media may not be applicable to specific patients.	General recommendations	A18 Need for Personalised Information
F	我会考虑这些建议是否具体可行，以及是否适用于我的个人情况。一些笼统或者“一刀切”的建议可能并不适合每个人。	I will consider whether the recommendations are concrete and feasible and whether they apply to my personal situation. Some general or ‘one-size-fits-all’ recommendations may not work for everyone.	Consider specific feasibility	A30 Perception of Information Feasibility
H	这种情况下，我会更倾向于相信官方发布的信息，比如疾控中心或者卫生部门的公告。	In this case, I would be more inclined to trust official information, such as announcements from the CDC or health authorities.	Believe the official release information	A2 Source Preference
E	如果作者在相关领域有深厚的研究经验或临床实践，那么他们的观点通常更值得信赖。	Authors are often more trustworthy if they have deep research experience or clinical practice in the relevant field.	Author’s professional background	A6 Source Expertise Perception
D	某些人或组织可能出于商业利益或者吸引关注度的目的，故意制造一些惊人的健康“发现”或者建议。	Some people or organisations may deliberately create some surprising health ‘discoveries’ or recommendations for commercial gain or to attract attention.	Commercial profit motive	A34 Perception of Social Media Commercialisation
B	我觉得这种算法推荐还挺准确的，经常能推送一些我感兴趣的健康话题。	I think this kind of algorithm recommendation is quite accurate, and I can often push some health topics that I am interested in.	Algorithmic recommendations are accurate	A48 Evaluation of Algorithmic Recommendations
I	我通常希望能够获得一些实用的建议和具体的行动方案。纯粹的知识固然重要，但我更希望能够找到一些可以立即付诸实践的方法。	I usually want to be able to get some practical advice and concrete courses of action. Pure knowledge is important, but I’d rather find something that I can put into practice right away.	Would like to get practical advice and ways to put it into practice right away	A7 Information Usefulness Perception
K	但如果是一些颠覆性的说法，或者与主流医学观点有很大出入的信息，我会更加谨慎。	But if it’s something subversive, or information that is very different from mainstream medical opinion, I’ll be more cautious.	Be more cautious with information that is subversive or at odds with mainstream medical opinion	A54 Willingness to Adopt Health Information
I	我们应该培养批判性思维，学会分辨信息的可靠性。	We should develop critical thinking and learn to discern the reliability of information.	Develop critical thinking	A40 Information Literacy

……

Table 5.2: Open Coding Process: Example Page from Interview Analysis

Notably, theoretical saturation was achieved within the first six interviews, with no new substantive codes emerging from subsequent interviews. This observation aligns with established methodological literature suggesting that basic elements of meta-themes typically emerge within six interviews (Guest et al., 2006).

5.2.1.2 Axial Coding

The axial coding phase involved re-categorisation and integration of the concepts generated during open coding, following the analytical framework established by Corbin and Strauss (2015). This process aimed to identify meaningful relationships between categories and their subcategories, ultimately leading to the emergence of nine main categories, as presented in Table 5.3:

The analysis focused on identifying causal relationships, intervening conditions, and consequences within the data. Through this process, the initial 57 open codes were grouped into more abstract conceptual categories that reflected the broader patterns and relationships in the data. Each main category was carefully defined and supported by multiple subcategories, ensuring a comprehensive representation of the phenomena under study.

Main Category	Corresponding Categories	Definition
Information Quality Factors	A4 Information Quality Perception	The subjective assessment of the overall quality and reliability of health-related information encountered on social media platforms.
	A5 Information Type Preference	The inclination towards specific formats or categories of health information on social media, such as text, images, or videos.
	A18 Need for Personalised Information	The desire for tailored health information that is relevant to one's specific health conditions, interests, or circumstances.
	A29 Concern about Social Media Information Quality	The level of apprehension or doubt regarding the accuracy and reliability of health information disseminated through social media channels.
	A30 Perception of Information Feasibility	The extent to which individuals believe that the health information provided on social media can be practically applied or implemented in their daily lives.
	A41 Perception of Information Understandability	The degree to which users find health-related information on social media comprehensible and accessible to their level of health literacy.
	A50 Information Presentation	The manner in which health information is structured, formatted, and displayed on social media platforms, influencing its accessibility and appeal to users.
Information Source Factors	A2 Source Preference	The tendency to favour certain types of information sources over others when seeking health-related information on social media.
	A3 Source Credibility Perception	The degree to which users perceive the reliability and trustworthiness of various health information sources on social media platforms.
	A6 Source Expertise Perception	The extent to which users recognise and value the professional knowledge and qualifications of health information providers on social media.
Information Channel Factors	A1 Channel Preference	The inclination towards specific social media platforms or features for accessing and consuming health-related information.
	A10 Information Acquisition Channels	The various social media platforms and features utilised by users to access and gather health-related information.
	A15 Information Acquisition Method	The specific strategies and techniques employed by users to search for, filter, and collect health information on social media platforms.
	A19 Information Overload	The state of being exposed to an excessive amount of health-related information on social media, potentially leading to confusion or decision paralysis.
	A20 Impact of Social Media on Information Acquisition	The ways in which social media platforms shape and influence the process of seeking and obtaining health-related information.

Main Category	Corresponding Categories	Definition
	A22 Perception of Social Media Timeliness	The degree to which users perceive social media as a source of up-to-date and current health information.
	A23 Perception of Social Media Comprehensiveness	The extent to which users believe social media provides a complete and thorough coverage of health-related topics.
	A24 Perception of Social Media Convenience	The degree to which users find social media platforms easy and efficient for accessing health information.
	A25 Perception of Social Media Diversity	The extent to which users perceive social media as offering a wide range of perspectives and information sources on health-related topics.
	A34 Perception of Social Media Commercialisation	The awareness and understanding of commercial interests and sponsored content within health-related information on social media platforms.
	A35 Need for Professionalism in Social Media Information	The desire for health information on social media to be presented and curated by qualified professionals or authoritative sources.
	A36 Overall Evaluation of Social Media Health Information	The holistic assessment of the quality, reliability, and usefulness of health-related information available on social media platforms.
	A44 Preference for Short Video Information	The inclination towards consuming health-related information in the format of brief, easily digestible video content on social media platforms.
	A48 Evaluation of Algorithmic Recommendations	The assessment of the relevance and quality of health information suggested by social media algorithms based on user behaviour and preferences.
Perceived Usefulness	A7 Information Usefulness Perception	The degree to which users believe that health information obtained from social media will enhance their health-related knowledge or decision-making.
	A14 Information Impact on Personal Life	The perceived effect of health information acquired from social media on an individual's daily habits, choices, and overall lifestyle.
	A16 Information Acquisition Purpose	The specific motivations and objectives driving users to seek health-related information on social media platforms.
	A17 Information Application Scenarios	The various contexts and situations in which users intend to apply the health information obtained from social media.
	A55 Benefit from Social Media Health Information	The perceived advantages and positive outcomes resulting from the consumption and application of health information found on social media platforms.
	A8 Information Evaluation Behaviour	The process by which users critically assess and judge the credibility and relevance of health information encountered on social media.

Main Category	Corresponding Categories	Definition
Health Information Adoption	A42 Failure to Adopt Health Information Behaviour	The instances and reasons why users do not implement or act upon health information obtained from social media platforms.
	A54 Willingness to Adopt Health Information	The readiness and intention of users to incorporate and apply health-related information from social media into their lives and decision-making processes.
Recipient Factors	A11 Perception of Medical Field	The general understanding and awareness of medical advancements, practices, and concepts that influence how users interpret health information on social media.
	A12 Attention to Health Information	The level of interest and focus users dedicate to health-related content encountered on social media platforms.
	A27 Attitude towards Information Acquisition	The overall disposition and approach users adopt when seeking and consuming health information on social media.
	A32 Emotional Response to Social Media Health Information	The affective reactions and feelings evoked in users when encountering health-related content on social media platforms.
	A37 Need for Information Literacy	The recognised importance of developing skills to critically evaluate, understand, and effectively use health information found on social media.
	A38 Level of Knowledge	The extent of an individual's existing understanding and familiarity with health-related topics and concepts encountered on social media.
	A39 Impact of Knowledge on Attitude	The way in which an individual's existing health knowledge shapes their perspective and reception of health information on social media.
	A40 Information Literacy	The capacity to locate, evaluate, and effectively use health information encountered on social media platforms.
	A45 Impact of Experience on Attitude	The way in which past interactions with health information on social media shape an individual's current approach and receptivity to such information.
	A46 Attitude Change	The shift in an individual's perspective or behaviour regarding health issues as a result of information encountered on social media platforms.
	A51 Personal Factors	The individual characteristics, circumstances, and experiences that influence how a person interacts with and responds to health information on social media.
Personal and Professional Factors	A9 Occupation and Information Exposure	The relationship between an individual's professional role and their exposure to, interpretation of, and response to health information on social media.
	A13 Information Impact on Profession	The perceived effect of health information from social media on an individual's professional practices, knowledge, or decision-making within their occupation.

Main Category	Corresponding Categories	Definition
	A49 Family Factors	The influence of family dynamics, roles, and responsibilities on an individual's engagement with and application of health information from social media.
Social Influencing Factors	A21 Purpose of Social Media Use	The primary intentions and objectives that drive individuals to engage with social media platforms for health information acquisition and sharing.
	A28 Impact of Pandemic on Information Dissemination	The ways in which global health crises, such as pandemics, alter the patterns, content, and reception of health information on social media platforms.
	A33 Perception of Social Media's Impact on Public Health	The perceived role and effectiveness of social media in shaping public health awareness, behaviours, and outcomes on a broader societal level.
	A43 Information Sharing Behaviour	The tendencies and motivations of users to disseminate health-related information they encounter on social media to their personal networks.
	A53 Information Behaviour in Emergency Situations	The patterns of seeking, evaluating, and sharing health information on social media during critical health events or emergencies.
Policy Recommendations and Future Outlook	A26 Expectations for Improving Social Media Health Information Environment	The desired changes and enhancements users hope to see in the quality, accessibility, and management of health information on social media platforms.
	A31 View on Responsibility of Information Dissemination	The opinions on who should be accountable for ensuring the accuracy and reliability of health information shared on social media platforms.
	A47 Future Outlook	The anticipated trends, challenges, and opportunities in the realm of health information dissemination and consumption on social media platforms.
	A52 Recommendation on Information Content	The suggestions and preferences expressed by users regarding the types, formats, and quality of health information they would like to see on social media.
	A56 Accountability	The identification of stakeholders and entities deemed responsible for the quality, accuracy, and ethical dissemination of health information on social media.
	A57 Policy Recommendations	The proposed guidelines, regulations, or interventions suggested to improve the management and quality of health information on social media platforms.

Table 5.3: Axial Coding Results: Interview Analysis

5.2.1.3 Selective Coding

Selective coding, the final stage in the grounded theory analytical process, focused on integrating and refining the theoretical relationships that emerged from the previous coding phases (Corbin and Strauss, 2008). Through iterative analysis and theoretical abstraction, six core categories emerged as fundamental to understanding health information adoption on social media platforms:

1. Information Quality Factors
2. Information Source Factors
3. Information Channel Factors
4. Recipient Factors
5. Perceived Usefulness
6. Health Information Adoption

These core categories were integrated into a preliminary theoretical model, as shown in Figure 5.1, which extends beyond traditional technology acceptance frameworks while maintaining theoretical parsimony. The model posits that Information Quality Factors, Information Source Factors, Information Channel Factors, and Recipient Factors function as antecedent variables influencing Perceived Usefulness. Perceived Usefulness, in turn, directly influences Health Information Adoption. This structure acknowledges that individual characteristics and capabilities play a direct role in shaping how users perceive the usefulness of health information, alongside the characteristics of the information itself and its delivery channels.

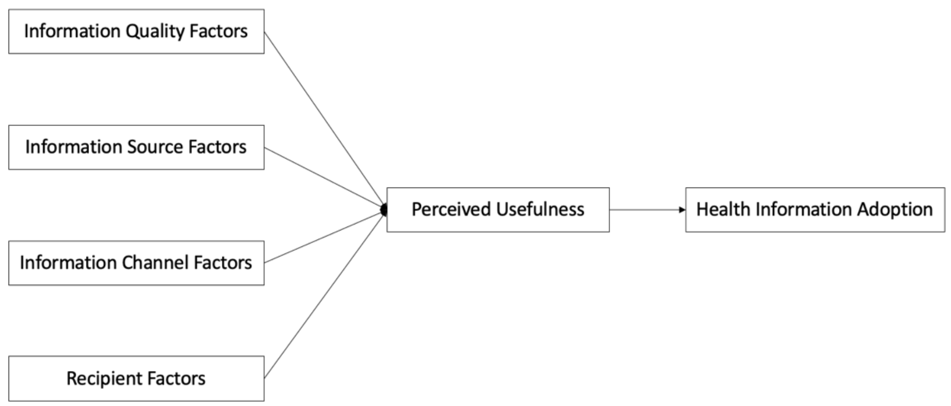

Figure 5.1: Core Categories of Interview Transcripts Relationship Diagram

The interview data yielded additional categories related to personal, professional, and social factors, but these were identified as contextual conditions rather than core theoretical components. These contextual categories align with the study's secondary research objectives: Personal and Professional Factors provide insights into individual-level variables that shape information processing and adoption (Research Objective 2); Social Influence Factors clarify the broader social dynamics affecting information dissemination and adoption patterns (Research Objective 3); Policy and Future Outlook categories inform the development of governance strategies for managing health-related misinformation (Research Objective 4).

5.2.2 Interpretation of Interview Findings

The analysis of interview data reveals a complex interplay of factors that influence health information adoption on social media platforms. Through systematic coding and analysis, six major themes emerged: information quality factors, information source factors, information channel factors, recipient factors, perceived usefulness, and health information adoption.

Before examining these factors in detail, it is essential to clarify the conceptual distinction between 'information source' and 'information channel', as these terms are often conflated in health information literature, particularly in social media contexts.

Throughout this analysis, ‘information source’ refers specifically to the creator or publisher of health information (such as healthcare professionals, research institutions, or individual users), whilst ‘information channel’ denotes the medium or platform through which information is transmitted, including its distinctive architectural and functional characteristics, such as WeChat, Douyin, Weibo, and their respective features. This distinction is particularly important in social media environments where multiple information sources may operate on the same platform, necessitating separate analysis of source credibility and platform attributes. The systematic categorisation presented in Table 5.3: Axial Coding Results reflects this conceptual separation, allowing for more subtle analysis of how different factors influence health information adoption.

5.2.2.1 Information Quality Factors

The analysis reveals that information quality in health-related social media content operates through multiple dimensions, with their relative importance varying across different user segments. These dimensions interact dynamically to influence users’ overall quality perception and subsequent information adoption behaviour within the unique context of social media communication.

Scientific rigour and evidence base emerge as fundamental components of information quality, particularly emphasised by users with professional backgrounds. As Researcher E articulates: “*Sufficient research support and data backing. If a health recommendation is supported by large-sample, long-term clinical studies, its credibility would greatly increase*.” This emphasis on empirical evidence reflects the increasing sophistication of social media users in evaluating health information, though the depth of such evaluation varies significantly across user groups. The finding suggests a growing awareness of the importance of evidence-based health communication, even in the rapid-paced social media environment.

Comprehensiveness and balance of information presentation constitute another crucial dimension of quality. Doctor A's observation captures this aspect: "*Credible health information should include comprehensive content, rather than being one-sided or taken out of context. If a piece of information only emphasises one viewpoint whilst neglecting other possible explanations or related factors, I would doubt its reliability.*" This finding indicates that users are becoming more discerning about potential bias in health information, seeking balanced perspectives rather than simplified narratives. The challenge of maintaining comprehensiveness whilst adapting to social media's inherent brevity creates a unique tension in health communication.

The temporal relevance and currency of information emerge as increasingly critical factors in the social media context. Doctor A emphasises: "*Medical knowledge is constantly updating, so the publication time of information is also very important. Information from a few years ago may no longer apply to the current situation.*" This temporal dimension highlights a particular challenge in social media health communication: balancing the need for current information against the platform's tendency to recirculate older content. The rapid evolution of medical knowledge creates additional complexity in maintaining information accuracy over time.

Communication style and accessibility significantly influence quality perception, though with notable variations across user groups. News Editor C provides insight into the professional perspective: "*I also pay attention to the language style of the information. Professional, objective expressions are usually more credible than emotional, exaggerated language.*" However, this preference for professional language must be balanced against accessibility needs, as illustrated by University Student H: "*I think I might want more specific advice and action plans. Pure knowledge might be too dry for me; I prefer things I can directly apply.*" This tension between professional rigour and practical accessibility emerges as a central challenge in social media health communication.

The analysis reveals distinct patterns in quality assessment across different user segments. Professional users, such as Researcher E and Professor F, demonstrate a strong emphasis on methodological rigour and scientific validity, frequently scrutinising the evidence base and analytical framework of health information. In contrast, non-professional users, exemplified by Housewife L, prioritise practical applicability and comprehensibility, focusing on the potential for direct implementation in daily life. This divergence suggests the need for layered communication strategies that can simultaneously satisfy both technical accuracy and practical utility requirements.

The findings indicate that information quality assessment in social media health communication is more subtle than traditional frameworks suggest, incorporating both objective criteria and subjective elements. The social media environment's unique characteristics—including rapid information flow, content fragmentation, and diverse audience composition—create specific challenges for maintaining and assessing information quality. Moreover, the significant variation in quality perception across user groups highlights the importance of considering audience segmentation in health communication strategies. The findings also suggest that information quality assessment cannot be isolated from source credibility and channel characteristics, indicating an interconnected system of quality evaluation in social media health communication.

5.2.2.2 Information Source Factors

The analysis reveals that source credibility in social media health communication manifests through multiple interrelated dimensions, each carrying a different weight across user segments. These dimensions operate within the unique dynamics of social media platforms, where traditional authority indicators interact with platform-specific credibility markers.

Professional expertise and authentic knowledge demonstration emerge as fundamental credibility indicators, though their interpretation varies across user groups. Doctor A emphasises this complexity: "*Correct and appropriate use of medical terms usually indicates that the information publisher has a relevant background. However, excessive use of professional terms, especially if used improperly, might be an attempt to appear knowledgeable.*" This observation reveals a sophisticated understanding among users of how expertise should be demonstrated in social media contexts, suggesting they have developed subtle skills in distinguishing genuine expertise from superficial displays of knowledge.

Institutional affiliation and organisational reputation constitute another crucial dimension of source credibility. Professor F articulates this perspective: "*If the information comes from an institution, I would consider the nature and reputation of that institution. For example, information from authoritative institutions like the World Health Organization or National Institutes of Health is usually more credible.*" This reliance on institutional reputation suggests that traditional authority structures maintain significant influence in social media environments, though their authority must be actively maintained through consistent, quality content delivery.

Academic credentials and research track records emerge as particularly significant for certain user segments, especially those with professional backgrounds. Researcher E emphasises: "*Academic reputation, for academic institutions or researchers, I would check the number and quality of their published papers, as well as their influence in the field.*" This finding indicates that traditional academic metrics retain importance in social media contexts, though their significance varies markedly across different user groups and platform types.

The analysis reveals a complex relationship between public reputation and sustained credibility in social media environments. Salesman G observes: "*Public reputation is also quite important; for example, in some well-known medical institutions or health-*

related official accounts, I tend to trust the information they publish." However, this trust in public reputation is increasingly tempered by critical awareness, as evidenced by Civil Servant I's warning: "*Public reputation is also important, but I think we should be cautious because sometimes even very famous people can spread misinformation.*" This tension between public prominence and actual reliability emerges as a particular challenge in social media health communication.

Transparency and conflict of interest disclosure appear increasingly critical in establishing source credibility. Professor F highlights this concern: "*I would check if the information source has potential conflicts of interest. For example, if a drug study is funded by a pharmaceutical company, I would be more cautious about its results.*" This finding suggests growing user sophistication in evaluating not just the information itself but also the potential motivations and biases of its sources.

The analysis reveals distinct patterns in how different user groups evaluate source credibility. Professional users, such as Researcher E and Professor F, demonstrate greater emphasis on formal credentials and research track records, frequently scrutinising academic qualifications and publication histories. In contrast, non-professional users, exemplified by University Student H and Housewife L, place greater weight on public reputation and perceived trustworthiness, often relying on collective user feedback and sustained performance over time.

These findings indicate that source credibility assessment in social media health communication is more complex than traditional models suggest, incorporating both conventional authority markers and platform-specific credibility indicators. The social media environment's unique characteristics—including rapid information dissemination, democratised content creation, and complex verification challenges—create specific demands for establishing and maintaining source credibility. Moreover, the observed variations in credibility assessment across user groups suggest the need for subtle approaches to establishing and maintaining source credibility in social media health communication, potentially requiring different strategies for different audience segments.

5.2.2.3 Information Channel Factors

The analysis demonstrates that social media platforms, as health information channels, operate through distinct yet interconnected characteristics that influence users' information reception and evaluation processes. These channel-specific features create unique opportunities and challenges for health information dissemination, with their impact varying across different user groups and information types.

Platform-specific affordances emerge as fundamental factors shaping health information dissemination and reception. News Editor C articulates this complexity: "*On WeChat, I follow many professional medical official accounts and regularly check their articles. On Weibo, there are many accounts of doctors and medical experts, and I often browse the health information they share. On Douyin, there are many health science popularisation bloggers who spread health knowledge in simple and easy-to-understand short videos.*" This observation reveals how different platforms' inherent characteristics create distinct information ecosystems, each supporting different modes of health communication and user engagement.

Content depth and format capabilities constitute crucial differentiating factors across platforms. Civil Servant I observes: "*WeChat official accounts usually provide longer articles that can explain a health issue in more detail. While short video platforms like Douyin often have more fragmented information, which might be more easily misunderstood.*" This insight highlights a fundamental tension in social media health communication: balancing comprehensive information delivery against platform-imposed format constraints. The finding suggests that users have developed a sophisticated understanding of how different platforms' structural characteristics influence information quality and reliability.

Information dissemination velocity and its implications emerge as significant considerations in platform evaluation. University Student H notes: "*Information spreads very quickly on Weibo, but rumours are also easy to appear.*" This observation reveals the double-edged nature of rapid information spread in social media environments, where the same mechanisms that facilitate the quick distribution of crucial health information can also accelerate the spread of misinformation. Users demonstrate awareness of this trade-off, developing platform-specific strategies for information verification.

Visual engagement capabilities and their impact on information comprehension represent another crucial dimension. Fitness Coach K reflects: "*Douyin focuses more on visual effects, so health information there is often more concise and eye-catching, but sometimes may lack depth.*" This finding indicates that while visual-centric platforms may enhance information accessibility and engagement, they may simultaneously pose challenges for conveying complex health information comprehensively. Users appear to consciously navigate this balance between engagement and depth.

The capacity of the platform to promote discussion and verification is becoming increasingly important. University Student H emphasises this aspect regarding one platform: "*Answers on Zhihu are usually longer, allowing for in-depth discussion, and there is a voting mechanism. I pay more attention to highly upvoted answers, especially those that provide detailed explanations and references.*" This finding suggests that platforms supporting substantive user interaction may facilitate stronger information verification processes through collective user engagement.

The analysis reveals varied preference patterns across user segments regarding channel selection. Professional users, such as Doctor A and Researcher E, demonstrate a preference for platforms supporting detailed content delivery and professional discourse. In contrast, general users like Retiree J express a preference for platforms with clearer information hierarchies: "*For important health information, I might be more inclined to trust long articles on WeChat official accounts, as they usually provide more context and explanation.*"

A particularly noteworthy finding emerges regarding algorithmic influence on information exposure. Professor F raises this concern: "*The most frightening thing is information cocoons. Social media algorithms may cause us only to see information that aligns with our own views, affecting comprehensive understanding.*" This observation reveals growing user awareness of how platform algorithms might create echo chambers, potentially limiting exposure to diverse health perspectives.

These findings indicate that channel characteristics in social media health communication operate through complex interactions between platform affordances, user preferences, and information types. The social media environment's distinct features—including varied format constraints, differential interaction capabilities, and algorithmic content curation—create specific challenges for effective health information dissemination. Moreover, the observed variations in channel preference and utilisation across user groups suggest the need for platform-specific communication strategies that account for both technical constraints and user expectations.

5.2.2.4 Recipient Factors

The analysis reveals that recipient characteristics manifest through complex interactions between cognitive capabilities, experiential backgrounds, and psychological dispositions in social media health information processing. These recipient factors operate dynamically within the social media environment, where traditional information processing patterns intersect with platform-specific engagement behaviours.

Knowledge foundation and health literacy emerge as fundamental factors shaping information evaluation capabilities. Researcher E articulates this complexity: "*I believe* *an individual's professional background, critical thinking ability, and familiarity with specific health fields all affect their ability to discern.*" This observation reveals how users' existing knowledge frameworks significantly influence their capacity to evaluate health information, suggesting that information processing operates through both domain-specific knowledge and general critical thinking skills.

Personal experience and established belief systems constitute crucial filters through which users process new health information. J, a Retiree, reflects this phenomenon: "*My judgement is mainly based on my personal experiences and official information I later learned about.*" This insight highlights how users' lived experiences create cognitive frameworks that influence their reception of new health information, potentially facilitating or hindering the adoption of novel health concepts depending on their alignment with existing experiential knowledge.

Critical thinking capabilities and information processing sophistication emerge as increasingly significant in the social media context. Civil Servant I demonstrates this awareness: "*Some information may look professional but could actually be incorrect. I try my best to discern, but I cannot say I am 100% capable. I think this requires long-term accumulation of knowledge and experience.*" This finding suggests that users recognise the complexity of health information evaluation, acknowledging both the importance of critical assessment skills and the challenges in developing these capabilities.

Emotional engagement and psychological responses represent crucial dimensions in information processing. University Student H articulates this dynamic: "*If I encounter such a situation, I usually stop and think about which statement aligns more with my common sense or previously learned knowledge. If I really cannot judge, I might search for more authoritative explanations.*" This observation reveals how users actively manage emotional responses to conflicting information, developing personal strategies for resolving information uncertainty and cognitive dissonance.

Individual health needs and personal relevance emerge as powerful drivers of information engagement. Housewife L emphasises this aspect: "*The main thing is to obtain truly useful information without wanting to be distracted by too many irrelevant things.*" This finding indicates that personal health contexts significantly influence users' information selection and processing patterns, suggesting that relevance perception operates as a primary filter in information engagement.

The analysis reveals distinct patterns in information processing across different demographic segments. Age-related variations in information preferences and processing strategies emerge clearly, with younger users like University Student H demonstrating a preference for actionable content, while older users like Retiree J exhibit more cautious evaluation patterns prioritising official sources.

Particularly noteworthy is the emergence of metacognitive awareness among some users regarding their own cognitive biases. Professor F offers this insight: "*People tend to believe information that aligns with their existing cognition or expectations, which may lead to the widespread dissemination of some inaccurate health information.*" This observation suggests that some users actively recognise and attempt to compensate for cognitive biases in their information processing.

These findings indicate that recipient factors in social media health communication operate through complex interactions between cognitive capabilities, experiential backgrounds, and psychological dispositions. The social media environment's unique characteristics—including information abundance, rapid dissemination, and diverse content formats—create specific demands on users' information processing capabilities. Moreover, the observed variations in processing patterns across user groups suggest the need for targeted communication strategies that account for different cognitive capabilities, experiential backgrounds, and psychological dispositions in health information dissemination.

5.2.2.5 Perceived Usefulness

The analysis demonstrates that perceived usefulness in social media health information manifests through multiple dimensions that reflect users' practical needs, professional requirements, and personal health objectives. These perceptions operate within the unique context of social media platforms, where traditional utility assessments interact with platform-specific information consumption patterns.

Practical applicability emerges as a fundamental dimension of perceived usefulness, particularly salient in everyday health management contexts. University Student H articulates this priority: "*I think I might be more hoping to get some specific advice and action plans. Pure knowledge might be too boring for me; I prefer things I can directly apply.*" This observation reveals how users increasingly value information that bridges the gap between theoretical knowledge and practical implementation, suggesting a growing emphasis on actionable health insights in social media contexts.

Personal relevance and need alignment constitute crucial factors in usefulness assessment. Housewife L demonstrates this perspective: "*The main thing is to obtain truly useful information without wanting to be distracted by too many irrelevant things.*" This finding indicates that users actively filter health information based on its alignment with their personal health contexts and immediate needs, suggesting that perceived usefulness operates as a primary criterion in information selection and retention.

Professional development utility emerges as particularly significant for users in health-related fields. Fitness Coach K articulates this dual requirement: "*I hope to gain professional knowledge, including some latest research findings or theoretical updates. Secondly, practical advice and tips that can be directly applied to my teaching.*" This observation reveals how professional users evaluate usefulness through both knowledge advancement and practical application lenses, suggesting a more complex utility assessment framework among this user segment.

Health outcome potential represents a crucial dimension in usefulness evaluation. News Editor C reflects this comprehensive perspective: "*This information can help me better understand my health condition, prevent and respond to various health issues, while also improving my health literacy and professional knowledge level.*" This finding suggests that users assess usefulness not only through immediate practical value but also through longer-term health management potential.

Information accessibility and implementation feasibility emerge as significant mediating factors in usefulness perception. Social Media Influencer D highlights this aspect: "*On Douyin, there are many health science popularisation bloggers who spread health knowledge in simple and easy-to-understand short videos. I find them interesting and practical.*" This observation reveals how platform-specific content characteristics can enhance or diminish perceived usefulness through their impact on information accessibility and engagement.

The analysis reveals distinct patterns in usefulness assessment across different user segments. Professional users, exemplified by Researcher E, demonstrate greater emphasis on scientific depth and theoretical advancement. In contrast, general users like Housewife L prioritise immediate practicality and straightforward implementation potential. This variation suggests that perceived usefulness operates through different frameworks across user groups, influenced by their respective needs and capabilities.

These findings indicate that perceived usefulness in social media health communication operates through complex interactions between practical needs, professional requirements, and personal health objectives. The social media environment's distinct features—including varied content formats, diverse user needs, and different engagement patterns—create specific challenges for delivering useful health information. Moreover, the observed variations in usefulness assessment across user groups suggest the need for differentiated content strategies that can simultaneously address multiple utility dimensions while maintaining information integrity and accessibility.

5.2.2.6 Health Information Adoption

The analysis reveals that health information adoption in social media contexts operates through a complex process influenced by multiple interacting factors rather than through simple linear acceptance or rejection. This adoption process reflects sophisticated decision-making patterns that integrate credibility assessment, personal relevance, and practical feasibility within the unique dynamics of social media platforms.

Scientific credibility and source reliability emerge as fundamental factors in adoption decisions. Doctor A articulates this rigorous evaluation approach: "*If the information cites specific research or data, I will look up the original literature. The scale of the study, research design, journal of publication, etc., all influence my judgment.*" This observation reveals how users, particularly those with professional backgrounds, employ sophisticated verification strategies in their adoption decisions, suggesting that information adoption in social media contexts increasingly demands robust evidence support.

Individual context and personal applicability constitute crucial dimensions in adoption consideration. Fitness Coach K emphasises this contextual complexity: "*Health advice is often not universally applicable; it needs to be judged based on individual health conditions, age, constitution, and other factors.*" This finding indicates that users actively evaluate health information against their personal circumstances, suggesting that adoption decisions incorporate both information credibility and individual relevance assessments.

Social validation and collective experience emerge as significant influences in the adoption process. Civil Servant I reflects this social dimension: "*If I see many positive* *comments under a piece of health information, especially if people share their personal experiences, I might be more inclined to believe this information.*” This observation reveals how social media’s interactive features create unique validation mechanisms through collective user experiences, though users demonstrate varying degrees of reliance on such social proof.

Implementation feasibility and practical constraints represent crucial considerations in adoption decisions. Salesman G articulates this practical perspective: “*Although health advice on social media sounds good, it is not suitable or easily achievable for everyone. You have to consider your actual situation.*” This finding suggests that users evaluate not only information credibility but also practical implementation barriers, indicating that adoption decisions incorporate both theoretical acceptance and practical feasibility assessments.

Platform characteristics and information presentation emerge as significant mediating factors in adoption processes. News Editor C demonstrates this platform-specific awareness: “*Articles on WeChat official accounts are usually longer and might be more comprehensive, but sometimes they also contain soft advertisements. Shares on Xiaohongshu feel more life-oriented but may lack professionalism.*” This observation reveals how platform-specific features influence adoption decisions through their impact on information comprehensiveness and credibility perception.

The analysis reveals a notably reflective dimension in the adoption process, highlighted by Nurse B’s observation: “*At the same time, it also made me realise that even good advice is meaningless if it can’t be effectively implemented. So now when I consider adopting a suggestion, I not only consider its reliability but also its feasibility in my life.*” This finding suggests that users develop increasingly sophisticated adoption frameworks through experience, integrating multiple evaluation criteria in their decision-making processes.

These findings indicate that health information adoption in social media contexts operates through complex interactions between credibility assessment, personal relevance, practical feasibility, and social validation. The social media environment's unique characteristics—including rapid information flow, diverse content formats, and interactive validation mechanisms—create specific challenges and opportunities for information adoption. Moreover, the observed sophistication in users' adoption decision-making suggests the need for comprehensive communication strategies that address multiple adoption barriers while leveraging platform-specific features to enhance adoption likelihood.

5.2.3 Summary of Interview Findings

The analysis of twelve in-depth interviews with diverse professional participants reveals a sophisticated ecosystem of factors influencing health information adoption on social media platforms. Rather than operating through simple linear relationships, these factors demonstrate complex interactions that collectively shape users' engagement with and adoption of health information. The findings outline six primary dimensions, each contributing uniquely to the overall health information adoption process whilst maintaining significant interconnections with other dimensions.

Information quality emerges as a foundational element, operating through multiple facets, including scientific rigour, comprehensiveness, timeliness, and practical relevance. Particularly noteworthy is the marked variation in quality perception between professional and non-professional users, with professionals emphasising empirical evidence and methodological soundness, whilst general users prioritise accessibility and practical applicability. This divergence suggests the need for multilayered communication strategies that can simultaneously satisfy different user segments' quality expectations.

Source credibility manifests through various mechanisms, including professional expertise demonstration, institutional reputation, and transparency in potential conflicts of interest. The findings reveal an increasingly sophisticated user understanding of source credibility, with participants demonstrating awareness of both traditional authority markers and the need for ongoing credibility validation in social media contexts. Users exhibit notable capability in recognising the limitations of even authoritative sources, suggesting evolved critical assessment skills in social media environments.

Channel characteristics demonstrate distinct influences across different social media platforms, with each platform’s inherent features creating unique opportunities and challenges for health information dissemination. The analysis reveals how platform-specific affordances shape both information presentation and user engagement patterns, highlighting the necessity of adapting health communication strategies to different platform environments. Particularly significant is the emergence of platform-specific information evaluation strategies among users.

Recipient factors emerge as crucial determinants of information processing and adoption, operating through complex interactions between knowledge levels, critical thinking capabilities, and experiential backgrounds. The findings emphasise how individual differences in these factors significantly influence users’ ability to evaluate and integrate health information, suggesting the importance of considering user diversity in health communication strategy development.

Perceived usefulness functions as a critical mediating mechanism between information characteristics and adoption behaviour. The analysis reveals how usefulness perceptions are shaped by both practical applicability and personal relevance, with notable variations across different user segments. This dimension emerges as particularly significant in bridging the gap between information exposure and adoption, suggesting its crucial role in effective health communication.

Health information adoption behaviour manifests as the culmination of these interacting dimensions, reflecting sophisticated decision-making processes that integrate multiple evaluation criteria. The findings reveal how adoption decisions incorporate assessments of information credibility, personal relevance, practical feasibility, and social validation, suggesting the need for comprehensive communication strategies that address multiple adoption barriers simultaneously.

These findings provide crucial insights into the mechanisms of health information dissemination and adoption within social media environments whilst establishing a robust theoretical foundation for subsequent quantitative investigation. The identified dimensions and their interactions suggest the need for subtle approaches to health communication that account for both the complexity of user evaluation processes and the unique characteristics of social media platforms. Moreover, these findings inform the development of the quantitative research phase by highlighting key variables and relationships requiring further systematic examination.

5.3 Social Media Comment Study Findings

This study employed a grounded theory approach to examine health-related comments across major social media platforms, providing deep insights into user behaviours and responses to health information in digital environments. The methodological choice aligns with the constructivist grounded theory framework (Charmaz, 2014), enabling the emergence of theoretical understanding from naturally occurring social media interactions.

The data collection process focused on three dominant social media platforms in China: WeChat, Douyin, and Weibo. These platforms were not only discussed in 2.2 but also emerged as primary channels for health information dissemination during the initial interview phase, representing diverse content-sharing mechanisms and user engagement patterns.

The sampling framework was structured around seven distinct domains of health information, as established in 2.3. These domains included information related to infectious diseases, non-communicable diseases, vaccines, diet and nutrition, drug and smoking, public health measures, and mental health. This comprehensive categorisation ensured the capture of diverse health topics and associated user responses across the digital health communication landscape. The selection criteria emphasised content relevance to health information, sufficient detail for meaningful analysis, temporal proximity within twelve months of data collection, and significant user engagement as indicated by responses and interactions. This structured approach to data collection enabled the capture of contextual information while maintaining methodological rigour.

Though resource-intensive, manual comment extraction proved essential for ensuring data quality and capturing the subtle aspects of user interactions with health information. This approach allowed researchers to maintain sensitivity to context and meaning, crucial elements in grounded theory research (Corbin and Strauss, 2008).

5.3.1 Data Analysis Process

Following the same grounded theory methodology applied in the interview analysis (5.2.1), this study presents the analysis of social media comments. This parallel analytical approach enabled meaningful comparison between interview insights and naturalistic social media behaviours while maintaining methodological consistency.

5.3.1.1 Open Coding

Employing the same analytical procedures described in 5.2.1.1, the initial analysis phase generated 50 distinct conceptual codes (designated with the letter ‘B’ plus numbers, e.g., B1, B2, B3). The analysis included comments ranging from brief responses to detailed discussions, ensuring the capture of both immediate reactions and considered reflections on health information.

To illustrate the systematic nature of the coding process, Table 5.4 presents a one-page excerpt from the complete 71-page comment analysis documentation and demonstrates the progression from raw data to conceptual codes.

评论提取	Extracted Comments	Conceptualisation	Categorisation
减肥专家的建议总是随大流改变，缺乏自己的核心理念。这种立场不稳的人值得信赖吗?	The advice of weight loss experts always follows the trend and lacks its own core philosophy. Is such a person with an unstable position trustworthy?	Unstable position	B1. Information Consistency
这篇健康文章虽然文笔流畅，但内容经不起推敲。很多说法都是道听途说，缺乏科学依据。	Although this health article is well written, the content does not stand up to scrutiny. Many of the claims are hearsay and lack scientific basis.	Lack of scientific evidence	B2. Information Accuracy
这个视频虽然介绍了这种健康食品的好处，但完全没有提到可能的副作用，信息不全面。	Although this video describes the benefits of this healthy food, it does not mention the possible side effects at all, and the information is not comprehensive.	The information is one-sided	B3. Information Completeness
这个健康频道的专家总是能把复杂的医学知识用通俗易懂的方式讲解出来，很受用。	The experts of this health channel are always able to explain complex medical knowledge in an easy-to-understand way, which is very useful.	Explain the profound in simple terms	B4. Information Adequacy
这个博主总是说一些玄乎其玄的养生理论，但从来不给出任何科学依据或研究支持。	This blogger always says some mysterious health theories, but never gives any scientific basis or research support.	Lack of factual basis	B5. Information Verifiability
这篇文章明显带有很强的个人偏见，作者对某些观点的批评太过激烈，缺乏客观分析。	The article is clearly highly biased, and the author's criticism of certain points of view is too fierce and lacks objective analysis.	The position is not objective enough	B6. Information Objectivity
这个公众号经常发布一些未经证实的传言，前几天还造谣某食品致癌。太不负责任了！	This public account often publishes some unconfirmed rumours, and a few days ago it also spread rumours that a certain food causes cancer. It's so irresponsible!	The source of the information is unreliable	B7. Information Reliability
这个营养师的建议太笼统了，没有考虑到不同人的体质差异，参考价值不大。	This dietitian's advice is too general and does not take into account the differences in the constitution of different people and has little reference value.	Ignoring individual differences	B8. Information Relevance
这个饮食建议考虑到了上班族的实际情况，给出了很多快手健康食谱，非常适用。	This dietary advice takes into account the actual situation of office workers and gives a lot of healthy recipes for fast hands, which is very applicable.	Fit for real	B9. Information Usefulness
这个减肥食谱的制作方法讲解得太复杂了，普通人很难照着做。应该给出一些简化版的建议。	The preparation method of this weight loss recipe is so complicated that it is difficult for ordinary people to follow it. Some simplified versions of the recommendations should be given.	Difficult to operate	B10. Information Operability
这个健康资讯平台总是第一时间发布疾控中心的最新通知，对疫情防控很有帮助。	This health information platform is always the first to publish the latest notices from the CDC, which is very helpful for epidemic prevention and control.	Timely announcements	B11. Information Timeliness
这个医学百科的释义太过学术化，对普通人来说很多地方看不明白。	The definition of this medical encyclopaedia is too academic, and many places are incomprehensible to ordinary people.	The explanation is too academic	B12. Information Understandability
这个医学数据库的搜索功能太简陋了，很难快速找到需要的信息。	The search function of this medical database is so rudimentary that it is difficult to quickly find the information you need.	The search function is not good	B13. Information Accessibility
这个健康节目邀请了很多名人来分享经历，增添了不少看点。	This wellness show invited many celebrities to share their experiences, which added a lot of highlights.	Celebrities share attraction	B14. Information Interestingness

Table 5.4: Open Coding Process: Example Page from Comment Analysis

After analysing approximately 500 comments, theoretical saturation was achieved, with no new substantive codes emerging from subsequent data. However, the researcher continued the analysis to nearly 1,000 comments to ensure comprehensive coverage and enhance the robustness of the findings. Through this process, 983 comments were analysed.

5.3.1.2 Axial Coding

Following the same analytical procedures outlined in 5.2.1.2, the axial coding phase integrated the concepts from open coding into six main categories, as presented in Table 5.5. The original 50 open codes were systematically grouped into more abstract conceptual categories that reflected the broader patterns and relationships in the data.

Main Category	Corresponding Categories	Definition
Information Quality Factors	B1 Information Consistency	The degree to which health information aligns with previously received or existing knowledge.
	B2 Information Accuracy	The extent to which health information is free from errors and precisely reflects factual reality.
	B3 Information Completeness	The degree to which health information covers all necessary aspects of a topic without significant omissions.
	B4 Information Adequacy	The sufficiency of health information in addressing the user's informational needs or questions.
	B5 Information Verifiability	The ease with which users can confirm or cross-check the accuracy of health information from other sources.
	B6 Information Objectivity	The degree to which health information is presented without bias, personal opinions, or vested interests.
	B7 Information Reliability	The consistency and dependability of health information across different instances or sources.
	B8 Information Relevance	The extent to which health information is applicable and pertinent to the user's specific situation or needs.
	B9 Information Usefulness	The practical value and applicability of health information in addressing users' health-related concerns or goals.
	B10 Information Operability	The ease with which users can apply or implement the health information in their daily lives or health practices.
	B11 Information Timeliness	The currency and relevance of health information with respect to the latest developments or user needs.
	B12 Information Understandability	The clarity and comprehensibility of health information for the intended audience.
	B13 Information Accessibility	The ease with which users can locate, retrieve, and access health information when needed.
	B14 Information Interestingness	The degree to which health information captures and maintains the user's attention and curiosity.
	B15 Information Attractiveness	The visual appeal and engaging nature of how health information is presented.
	B16 Cultural Sensitivity	The extent to which health information respects and accommodates diverse cultural backgrounds and perspectives.
Information Source Factors	B17 Source Expertise	The level of knowledge, skills, and experience possessed by the provider of health information.
	B18 Source Authoritativeness	The recognised standing or official status of the health information source within the healthcare community.
	B19 Source Reliability	The consistency and dependability of a particular source in providing accurate health information over time.
	B20 Source Affinity	The degree of emotional connection or relatability users feel towards the health information source.

Main Category	Corresponding Categories	Definition
	B21 Source Transparency	The openness and clarity with which the source discloses its identity, intentions, and potential conflicts of interest.
	B22 Social Proof	The influence of others' actions or opinions on an individual's acceptance of health information.
	B23 Trust in Healthcare System	The level of confidence individuals has in the overall healthcare system and its ability to provide reliable health information.
	B24 Social Norms	The perceived standards or expectations within a social group regarding health information and behaviours.
Information Channel Factors	B25 Channel Professionalism	The degree to which the medium conveying health information maintains high standards of quality and conduct.
	B26 Channel Accessibility	The ease with which users can access and navigate the platform or medium providing health information.
	B27 Channel Interactivity	The extent to which the medium allows for two-way communication and user engagement with health information.
	B28 Channel Reliability	The consistency and dependability of the medium in delivering accurate and timely health information.
	B29 Channel Functionality	The range and effectiveness of features offered by the medium for accessing and using health information.
	B30 Channel Dependency	The extent to which users rely on a particular medium as their primary source of health information.
	B31 Channel Sociability	The capacity of the medium to facilitate social interactions and information sharing among users.
	B32 Channel Profitability	The perceived commercial interests or financial motivations behind the medium providing health information.
	B33 Privacy Concerns	The level of worry or unease regarding the protection and use of personal health information.
	B34 Ethical Considerations	The moral implications and principles considered in the creation, dissemination, and use of health information.
Perceived Usefulness	B35 Perceived Usefulness	The degree to which an individual believes that using the health information will enhance their health outcomes or knowledge.
	B36 Emotional Resonance	The extent to which health information evokes emotional responses or connects with the user's feelings.

Main Category	Corresponding Categories	Definition
	B37 Peer Influence	The impact of friends, family, or social connections on an individual's acceptance and use of health information.
	B38 Perceived Long-term Benefits	The anticipated positive outcomes or advantages of adopting health information over an extended period.
Recipient Factors	B39 Level of Knowledge	The existing understanding and awareness an individual possesses about health-related topics.
	B40 Information Processing Ability	The capacity to comprehend, analyse, and apply health information effectively.
	B41 Health Literacy Level	The degree to which individuals can obtain, process, and understand basic health information to make appropriate health decisions.
	B42 Previous Health Experiences	The impact of past encounters with healthcare systems or health issues on current health information reception and use.
	B43 Perceived Health Status	An individual's subjective assessment of their own health condition and its influence on health information seeking and adoption.
	B44 Information Seeking Behaviour	The patterns and strategies individuals employ to search for and obtain health-related information.
	B45 Cognitive Involvement	The degree of personal relevance and mental engagement an individual experiences when processing health information.
	B46 Perceived Risk	The subjective evaluation of potential negative consequences associated with adopting or not adopting health information.
	B47 Information Overload	The state of being exposed to excessive amounts of health information, leading to difficulty in processing or decision-making.
	B48 Information Consistency with Personal Beliefs	The extent to which health information aligns with an individual's pre-existing values, attitudes, and worldviews.
Health Information Adoption	B49 Health Information Adoption	The process by which individuals incorporate health information into their knowledge, attitudes, or behaviours.
	B50 Information Sharing Behaviour	The tendency and methods individuals use to disseminate health information within their social networks.

Table 5.5: Axial Coding Results: Comment Analysis

5.3.1.3 Selective Coding

Through the same selective coding process as detailed in 5.2.1.3, six core categories emerged:

1. Information Quality Factors
2. Information Source Factors
3. Information Channel Factors
4. Perceived Usefulness
5. Recipient Factors
6. Health Information Adoption

These core categories were integrated into a preliminary theoretical model, as shown in Figure 5.2, which extends beyond traditional technology acceptance frameworks while maintaining theoretical parsimony. The model posits that information quality factors, information source factors, and information channel factors function as antecedent variables that influence perceived usefulness. Perceived Usefulness, in turn, directly influences Health Information Adoption. Of particular note is the unique positioning of Recipient Factors within this model. Based on the analysis of social media comments, Recipient Factors demonstrate potential moderating effects on the relationships between other variables. Consequently, Recipient Factors are positioned as a potential moderating variable in this preliminary relationship model.

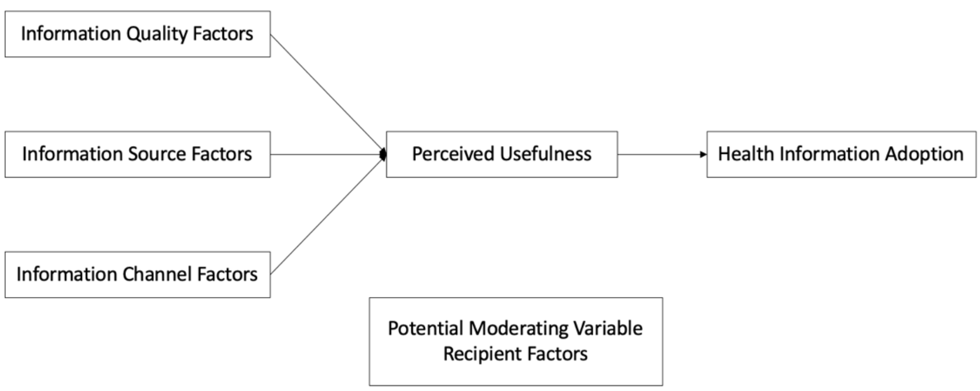

Figure 5.2: Core Categories of Extracted Comments Relationship Diagram

While the comment data analysis largely corroborates the findings from the interview phase, it also provides distinct insights into how users engage with health information in social media contexts. These complementary yet unique perspectives will be explored in detail in 5.4, where findings from both data sources are systematically integrated and compared.

5.3.2 Interpretation of Extracted Comment Findings

The analysis of social media comments reveals distinct patterns in how users naturally engage with and evaluate health information in their daily social media interactions. Unlike semi-structured interview responses, these spontaneous comments provide unique insights into users' immediate reactions and authentic concerns regarding health information. Through systematic analysis of these comments, six core categories emerged, mirroring yet distinctly characterising the dimensions identified in the interview analysis. These categories demonstrate the complex interplay between information characteristics, user perceptions, and platform dynamics in shaping health information adoption behaviours on social media.

5.3.2.1 Information Quality Factors

The analysis of social media comments reveals that information quality in health-related content manifests through a sophisticated interplay of multiple dimensions, with their relative importance shifting across different health topics and user contexts. These dimensions operate dynamically within the unique constraints and opportunities of social media platforms, shaping how users evaluate and interact with health information in their daily lives.

Information consistency and reliability emerge as paramount concerns in users' natural discourse. A particularly telling comment on vaccine-related information illustrates this priority: "*Another bunch of messy 'expert' opinions! Which statement is correct? A few days ago, they said the vaccine was ineffective, and today they say it is effective; it is so confusing.*" This spontaneous user reaction reveals the deep impact of information inconsistency on public trust and understanding, highlighting a critical challenge in social media health communication: maintaining consistent messaging whilst accommodating evolving scientific understanding.

The comprehensiveness and practical utility of health information constitute another crucial dimension, particularly evident in chronic disease management contexts. A detailed user comment about diabetic diet management provides valuable insight: "*It took several months to figure out how to eat. The doctor's advice was too general, and the information online was too chaotic. In the end, I found a detailed diet plan in a professional diabetes forum, including daily calorie allocation, food choices, etc. This kind of comprehensive information is really helpful, allowing me actually to implement it in daily life.*" This narrative demonstrates users' sophisticated understanding of what constitutes truly useful health information, emphasising the importance of both completeness and actionability in health communication.

Information timeliness and actionability emerge as critical factors, particularly in rapidly evolving public health situations. A user's response to updated public health measures captures this dynamic: "*Changed again? I surrender! But this time, it is explained quite clearly, specifying mask types and wearing occasions. At least now I know what to do, unlike before when it was so ambiguous.*" This comment reveals the complex relationship between information currency and practical guidance, suggesting that effective health communication must balance rapid updates with clear, implementable instructions.

The cultural dimension of health information quality presents unique challenges and opportunities in the globalised social media environment. An overseas Chinese user's comment on traditional Chinese medicine exemplifies this complexity: "*I was quite confused about what 'yin-yang balance' is, 'qi and blood harmony'... Although I am Chinese, I grew up abroad and do not really understand these concepts. But the article explained it in modern medical terms later, which was quite interesting.*" This observation highlights the importance of cultural sensitivity and translation in health communication, suggesting the need for sophisticated approaches that bridge traditional and modern medical paradigms.

The analysis reveals intricate tensions between various quality dimensions in the social media context. The challenge of balancing professional accuracy with general accessibility emerges as a persistent theme across user comments. This tension manifests particularly strongly in social media environments, where content must simultaneously maintain scientific rigour whilst engaging diverse audiences with varying levels of health literacy.

Moreover, the findings suggest that the relative importance of different quality dimensions varies significantly across health topics. In discussions of infectious diseases, users prioritise information timeliness and accuracy, reflecting the urgent nature of these health threats. Conversely, in chronic disease management discussions, users emphasise comprehensiveness and practical applicability, indicating the need for sustained, detailed guidance. This variation demonstrates the necessity of context-sensitive approaches to health information quality assessment and communication strategy development.

5.3.2.2 Information Source Factors

The analysis of social media comments reveals that source credibility in health information operates through multiple interconnected dimensions within the social media ecosystem. These dimensions manifest distinctively in users' spontaneous evaluations and discussions, reflecting the complex nature of source assessment in digital health communication.

Professional authority emerges as a fundamental yet subtle factor in users' source evaluation. A particularly illustrative comment reflects this complexity: "*Seeing that this advice was issued by the National Health Commission makes it feel much more* *reliable. Although I sometimes question official statements, they are at least more credible than those messy self-media.*" This response reveals a sophisticated understanding of source hierarchy in health information, where users maintain critical awareness while still recognising institutional authority. The tension between institutional credibility and individual scepticism represents a unique challenge in social media health communication.

Transparency and evidence-based practice emerge as crucial dimensions in building source credibility. A user's comment about a doctor blogger provides valuable insight: "*Recently, I have been following a doctor blogger who always attaches relevant research links when publishing health information. Although I cannot really understand those professional literature, I feel he is very rigorous in what he does, which is reassuring.*" This response highlights how transparency in information sourcing can enhance credibility even when the underlying evidence exceeds users' technical comprehension, suggesting a complex relationship between transparency and trust in social media health communication.

Social validation plays a distinctive role in source credibility assessment within social media environments. This dimension is captured in one user's comment: "*Everyone in our community group is forwarding this health preservation method, saying it is particularly effective. Although I have not tried it yet, seeing so many people recommend it makes me feel it should be fine.*" This observation reveals how collective endorsement can influence individual trust assessments, highlighting the unique social dynamics of source credibility in digital platforms.

The emotional resonance and personal authenticity of information sources emerge as significant factors in user engagement. A particularly telling comment illustrates this dimension: "*Recently, I have been following a doctor who has had cancer. His shared anti-cancer experiences are particularly genuine, feeling more convincing than those experts who only talk about theories.*" This response suggests that personal experience and emotional authenticity can sometimes outweigh formal credentials in establishing source credibility, particularly in social media contexts.

Broader institutional trust emerges as a foundational factor influencing source credibility assessment. A comment revealing systemic distrust provides critical insight: "*To be honest, I am distrustful of hospitals now. Always feel like being treated as a money-making machine when seeing a doctor, so even if it is said by a doctor, I will still compare from multiple sources.*" This observation highlights how institutional trust issues can complicate source credibility assessment in health communication, leading users to adopt more complex verification strategies.

The analysis reveals sophisticated patterns in how source credibility factors interact within the social media environment. A notable tension exists between professional authority and relatable authenticity. While users value professional credentials, they simultaneously seek sources that demonstrate personal understanding and genuine engagement. This creates a unique challenge in social media health communication: balancing professional credibility with authentic connection.

The importance of various source credibility factors appears to shift according to the health topic and context. In discussions of serious diseases or public health emergencies, institutional authority and professional credentials carry particular weight. Conversely, in discussions of lifestyle health and wellness, personal experience and social validation emerge as more influential factors. This variability suggests that effective health communication on social media requires a subtle understanding of how different source credibility dimensions interact with specific health contexts and user needs.

These findings suggest that source credibility in social media health communication is more dynamic and context-dependent than traditional frameworks might suggest. The spontaneous nature of social media comments reveals how users actively negotiate between different dimensions of source credibility in their everyday interactions with health information, highlighting the need for adaptable and context-sensitive approaches to establishing and maintaining source credibility in social media environments.

5.3.2.3 Information Channel Factors

The analysis of social media comments reveals that channel characteristics significantly shape how users encounter, evaluate, and engage with health information in digital spaces. These characteristics operate through multiple interconnected dimensions, creating unique opportunities and challenges for health communication in social media environments.

Platform professionalism and reliability emerge as foundational considerations in users' channel assessment. A particularly revealing comment illustrates this priority: "*Now I look at this doctor for health information, feeling their team is quite professional, and content review is strict. Unlike some platforms where all kinds of health rumours are believed.*" This observation highlights users' sophisticated understanding of platform differences in content governance and quality control. The emphasis on content review mechanisms suggests that users actively consider platform-level safeguards when evaluating health information reliability.

Technical functionality and user experience emerge as crucial factors in channel effectiveness. A user's detailed observation provides insight into this dimension: "*Recently used a new health app, the interface is concise, the search function is powerful, and it can recommend content based on personal situations. It is particularly easy to use.*" This response reveals how technical capabilities, particularly personalisation features, can enhance users' engagement with health information. The appreciation of user-centric design suggests that technical sophistication must be balanced with accessibility to facilitate health information dissemination effectively.

The interactive nature of social media platforms emerges as a distinctive advantage in health communication. A comment captures this unique characteristic: "*I like to look at health topics on this app because I can see different people's experiences and views, and sometimes can directly ask professionals. This kind of interaction gives me more confidence in the information.*" This observation reveals how interactive features can enhance information credibility through multi-dimensional verification and direct professional engagement, creating unique opportunities for collaborative learning in health communication.

Platform algorithms and user dependency patterns emerge as significant factors in information exposure. A particularly telling comment illustrates this dynamic: "*Actually, I mainly watch funny videos on Douyin, but the algorithm keeps pushing me some health tips. I have remembered them as I watch, feeling quite practical.*" This response reveals the complex interplay between platform algorithms and passive information acquisition, suggesting that channel characteristics can shape health information exposure even when users are not actively seeking such content.

Commercial interests and privacy concerns emerge as critical considerations in users' channel assessment. A comment highlighting these tensions provides valuable insight: "*These platforms are too good at doing business now; even watching a health video is full of advertisements. And I always feel like they are collecting my health data, and I am a bit worried about privacy issues.*" This observation reveals users' growing awareness of the commercial nature of social media platforms and their implications for health information integrity and personal privacy.

Ethical considerations and platform responsibility emerge as significant factors in channel evaluation. A user's pointed critique illustrates this dimension: "*Some platforms post all kinds of exaggerated health rumours for traffic. This kind of irresponsible behaviour really needs to be managed.*" This response highlights users' expectations for platform accountability in health information governance, suggesting that perceived ethical responsibility influences channel credibility.

The analysis reveals sophisticated patterns in how channel characteristics interact within the health information ecosystem. A notable tension exists between professional specialisation and social engagement. While professionally focused health platforms may offer higher quality information, general social media platforms offer greater reach and engagement. This creates a unique challenge in health communication: balancing information quality with accessibility and engagement.

The importance of various channel characteristics appears to shift across different user demographics and health contexts. Younger users demonstrate greater emphasis on interactive features and social integration, while older users prioritise ease of use and information reliability. Similarly, acute health concerns drive users toward more professional platforms, while general wellness information is more readily consumed through everyday social media channels. This variability suggests that effective health communication requires strategic channel selection based on target audience characteristics and health topic specificity.

These findings suggest that channel factors in social media health communication are more complex and influential than traditional health communication models might suggest. The spontaneous nature of social media comments reveals how platform characteristics actively shape users' health information experiences, highlighting the need for channel-sensitive approaches to health communication strategy.

5.3.2.4 Recipient Factors

The analysis of social media comments reveals that recipient characteristics operate as complex moderating forces in health information processing and adoption. These characteristics manifest through multiple dimensions, reflecting the dynamic nature of individual differences in health information engagement within social media environments.

Health literacy and knowledge sophistication emerge as fundamental moderating factors in information processing. A medical student's comment provides particular insight into this dimension: "*As a medical student, I find these so-called 'health secrets' laughable. But my friends all seem to believe them.*" This observation reveals how professional knowledge creates distinct patterns of information evaluation, highlighting the significant role of domain expertise in shaping critical assessment capabilities. The contrast between expert and lay perspectives suggests that health literacy levels create different thresholds for information acceptance.

Personal health experiences and conditions emerge as powerful contextual factors influencing information engagement. A particularly revealing comment illustrates this dynamic: "*Since I was diagnosed with diabetes, I have become particularly sensitive to dietary information. Before, I would just glance at it, but now I carefully verify whether it is suitable for my condition.*" This response demonstrates how personal health circumstances can fundamentally alter information processing patterns, creating more focused and critical engagement with health content. The transformation in information behaviour suggests that health status operates as a key motivational factor in information evaluation.

Cognitive load and information processing capacity emerge as crucial factors in users' engagement with health content. A comment capturing information overwhelm provides valuable insight: "*Recently, I have seen too many contradictory weight loss advice, leaving me completely confused about which to believe. I feel more confused the more I look; I might as well give up on losing weight.*" This observation reveals how cognitive overload can lead to information avoidance, suggesting that individual processing capacities significantly moderate information adoption patterns.

Prior beliefs and experiential knowledge emerge as significant filtering mechanisms in information evaluation. A user's resistance to new health claims illustrates this dimension: "*Although many people say certain foods are toxic, I have been eating them since childhood without any issues. I think these claims are exaggerated; I will just stick to my own habits.*" This response reveals how personal experience can create resistance to new information, highlighting the complex interaction between existing beliefs and information acceptance.

The temporal dynamics of recipient factors emerge as an important consideration in health communication. A comment about pandemic information fatigue provides crucial insight: "*When the pandemic first started last year, I paid attention to every piece of prevention information. Now I feel numb unless it's a particularly important notice; I am mostly too lazy to look.*" This observation reveals how recipient characteristics can shift over time, suggesting that information processing patterns are not static but respond to contextual changes and experience accumulation.

Information-seeking strategies emerge as distinctive patterns shaped by personal circumstances. A particularly telling comment illustrates this evolution: "*Since my family member was diagnosed with cancer, I started frequently using some professional medical websites. Articles I used to find too difficult to understand, I now study carefully.*" This response demonstrates how personal circumstances can drive changes in information processing capabilities and preferences, suggesting that recipient factors are dynamic rather than fixed characteristics.

The analysis reveals sophisticated patterns in how recipient factors moderate the influence of other variables in health information processing. A notable interaction exists between source credibility and personal experience, as illustrated by one user's comment: "*Even if it is said by an authoritative expert, if it completely contradicts my experience, I would still be sceptical. I might look into it from multiple perspectives.*" This observation suggests that recipient factors can override traditional credibility indicators, highlighting the complex nature of information evaluation in personal health contexts.

The importance of recipient factors appears to vary across different health topics and contexts. In technical medical information, knowledge levels and health literacy play particularly crucial roles. In lifestyle and preventive health information, personal beliefs and existing habits emerge as more significant moderators. This variability suggests that effective health communication requires careful consideration of how recipient characteristics interact with specific health contexts and information types.

These findings suggest that recipient factors in social media health communication operate as complex, dynamic moderators rather than simple demographic variables. The spontaneous nature of social media comments reveals how personal characteristics actively shape information processing and adoption patterns, highlighting the need for more subtle, recipient-centred approaches to health communication strategy.

5.3.2.5 Perceived Usefulness

The analysis of social media comments reveals that perceived usefulness operates as a critical mediating mechanism in health information adoption. This construct manifests through multiple interconnected dimensions, reflecting the complex nature of value assessment in social media health communication contexts.

Practical utility emerges as a fundamental dimension in users' assessment of health information value. A particularly revealing comment illustrates this priority: "*Recently, I saw a method for adjusting sleep patterns, tried it for a week, and really felt the effect. This kind of advice that can actually improve life is truly useful.*" This response highlights how immediate experiential validation shapes perceptions of usefulness, suggesting that practical applicability serves as a primary criterion in value assessment. The emphasis on tangible results indicates that users prioritise actionable information that demonstrates clear benefits in daily life.

Emotional resonance emerges as a distinctive dimension of perceived usefulness in social media contexts. A comment about cancer patient content provides valuable insight: "*That video of a cancer patient sharing their experience fighting cancer made me cry. Although I do not have cancer, his positive and optimistic attitude really inspired me. I feel I benefited a lot.*" This observation reveals how emotional impact can enhance perceived value beyond practical utility, suggesting that emotional engagement contributes significantly to information usefulness assessment in social media environments.

Social validation emerges as a powerful influence on perceived usefulness within networked environments. A dormitory-based observation illustrates this dynamic: "*Recently, everyone in our dormitory has been using a meditation app. My roommate said it is particularly effective for improving sleep. Although I have not felt it obviously, seeing everyone persist makes me think it must be quite useful.*" This response demonstrates how collective endorsement can shape individual perceptions of utility, highlighting the social nature of value assessment in digital contexts.

Long-term benefit assessment emerges as a sophisticated dimension in usefulness evaluation. A comment about dietary modification provides crucial insight: "*Recently, I have been adjusting my diet following a nutritionist's advice. Although I cannot see any changes in the short term, thinking about the benefits for future health makes it feel very worthwhile to persist.*" This observation reveals how anticipated future value influences current usefulness assessments, suggesting that temporal considerations play a significant role in information value perception.

The mediating role of perceived usefulness emerges clearly in the analysis. A particularly telling comment illustrates this mechanism: "*Sometimes, even if it is said by an authoritative expert if I feel it is not useful to me, I will not do it. Conversely, if I feel it is useful, even if it is an experience shared by an ordinary person, I am willing* *to try.*" This response demonstrates how perceived usefulness can override traditional credibility indicators, suggesting its central role in the adoption decision process.

Context dependency emerges as a significant feature of usefulness assessment. The analysis reveals how perceptions of utility shift across different health topics and situations. For acute symptoms, immediate effectiveness becomes paramount, while for preventive health behaviours, long-term benefit assessment takes precedence. This variability suggests that usefulness perception operates differently across various health contexts.

Environmental influence on perceived usefulness emerges as a notable finding. A comment about workplace influence provides valuable insight: "*I used to think exercise advice was not very useful, but since the company started encouraging employees to exercise, I suddenly found those suggestions became very valuable.*" This observation reveals how contextual changes can transform usefulness assessments, suggesting that perceived value is not static but responsive to environmental factors.

The analysis reveals sophisticated patterns in how perceived usefulness integrates with other factors in the health information adoption process. A notable interaction exists between practical utility and emotional resonance, where information that satisfies both dimensions appears particularly influential. This creates unique opportunities for health communication that can combine practical value with emotional engagement.

These findings suggest that perceived usefulness in social media health communication operates as a complex, context-dependent construct rather than a simple utility assessment. The spontaneous nature of social media comments reveals how users actively negotiate between different dimensions of value in their everyday health information interactions, highlighting the need for more subtle approaches to value creation in health communication strategy.

5.3.2.6 Health Information Adoption

The analysis of social media comments reveals that health information adoption manifests as a complex, multi-stage process within social media environments. This process operates through multiple interconnected phases, reflecting the sophisticated nature of health information integration in digital contexts.

Initial engagement emerges as a crucial first phase in the adoption process, often occurring through incidental exposure to social media environments. A particularly revealing comment illustrates this dynamic: "*While browsing through Douyin, I saw a doctor explaining how to prevent cervical spondylosis. It seemed reasonable, so I liked and saved it.*" This observation demonstrates how platform algorithms and user behaviour patterns create opportunities for health information discovery, suggesting that adoption often begins through passive rather than active information encounters.

Critical evaluation emerges as a sophisticated phase in the adoption process, where users actively assess information validity and relevance. A comment about weight loss claims provides valuable insight: "*I saw a weight loss method claiming to lose 10 pounds in a week. Although tempting, it is too exaggerated and does not seem credible. I still believe that slow and steady is healthier.*" This response reveals how users employ critical thinking and existing knowledge to filter information, suggesting that adoption decisions involve complex cognitive assessment processes.

Deliberative decision-making emerges as a distinct phase involving information verification and intention formation. A comment about intermittent fasting illustrates this process: "*Recently, I have seen many people recommending intermittent fasting. After looking into the scientific basis, it seems reasonable. I am planning to try it starting next week.*" This observation demonstrates how users engage in additional information-seeking before commitment, suggesting that adoption decisions often involve extended consideration rather than immediate acceptance.

Behavioural implementation emerges as the crucial actualisation phase of adoption. A particularly telling comment about dietary changes provides insight: "*Last month, I started adjusting my diet structure according to a nutritionist's advice. I have persisted for a few weeks now, and I really feel much better physically.*" This response reveals how successful adoption culminates in sustained behaviour change, suggesting that true adoption extends beyond mere information acceptance to actual lifestyle modification.

The non-linear nature of adoption emerges as a significant finding in the analysis. A comment about water consumption illustrates this complexity: "*Previously, I saw that you should drink eight glasses of water a day, and I persisted for a while. Later, I saw that drinking so much water is actually unnecessary, so now I just drink according to my thirst.*" This observation reveals how adoption decisions remain subject to revision based on new information or experience, suggesting that health information adoption operates as a dynamic rather than a static process.

Adoption patterns emerge as distinctly variable across different types of health information. The analysis reveals how simple lifestyle modifications may experience rapid adoption while complex behaviour changes face greater resistance. A comment about smoking cessation illustrates this challenge: "*I have seen a lot of advice on quitting smoking. I understand the reasoning, but it is really hard to implement. Maybe more support and incentive mechanisms are needed.*" This observation suggests that adoption difficulty varies significantly with behaviour complexity and addiction factors.

Social media influence on adoption emerges as a distinctive feature of digital health communication. A comment about peer influence provides crucial insight: "*Seeing many people in my friend circle showing off their weight loss results makes me a bit anxious, and I want to follow the trend and try it too.*" This response demonstrates how social comparison and visibility in digital platforms can accelerate adoption intentions, suggesting that social media characteristics create unique adoption pressures.

The analysis reveals sophisticated patterns in how various factors interact during the adoption process. A notable relationship exists between perceived usefulness and implementation difficulty, where highly useful information may still face adoption barriers due to practical challenges. This creates a complex dynamic where adoption success depends not only on information quality but also on implementation support.

These findings suggest that health information adoption in social media environments operates as a complex, dynamic process rather than a simple acceptance-rejection decision. The spontaneous nature of social media comments reveals how users navigate multiple phases of adoption while responding to various influences and barriers, highlighting the need for more comprehensive approaches to supporting health behaviour change through social media platforms.

5.3.3 Summary of Extracted Comments Findings

The systematic analysis of spontaneous social media comments reveals a complex ecosystem of factors influencing health information adoption in digital environments. These naturally occurring interactions provide unique insights into how users authentically engage with health information, demonstrating sophisticated evaluation processes that operate through multiple interconnected dimensions. The findings outline six primary dimensions that collectively shape users' natural information processing and adoption behaviours whilst maintaining significant dynamic interactions.

Information quality emerges as a fundamental dimension, operating through multiple facets, including accuracy, comprehensiveness, timeliness, and practical applicability. Particularly noteworthy is how users' quality assessment manifests differently in spontaneous interactions compared to structured evaluations, with immediate relevance and practical utility often taking precedence over technical accuracy. The findings reveal sophisticated user strategies for managing the tension between information reliability and accessibility, suggesting evolved evaluation mechanisms specific to social media environments.

Information source demonstrates complex manifestation patterns in natural social media interactions, operating through various mechanisms, including professional authority, experiential authenticity, and social validation. The analysis reveals how users actively negotiate between different forms of credibility, often weighing institutional authority against personal authenticity and collective endorsement. This sophisticated credibility assessment reflects users' adaptation to the unique challenges of evaluating health information sources in social media contexts.

Information channel emerge as fundamental shaping mechanisms, with different social media platforms creating distinct environments for health information dissemination and evaluation. The findings reveal how platform-specific features shape not only information accessibility but also user engagement patterns and evaluation strategies. Particularly significant is the emergence of platform-dependent trust mechanisms, where users develop platform-specific criteria for information assessment.

Recipient factors manifest as powerful moderating influences, operating through complex interactions between knowledge levels, personal experiences, and emotional states. The analysis reveals how these individual differences create distinct patterns of information processing and adoption, suggesting the need for more subtle approaches to health communication that account for user diversity. Particularly noteworthy is how recipient characteristics dynamically evolve through continued exposure to health information.

Perceived usefulness operates as a critical mediating mechanism, bridging the gap between information characteristics and adoption behaviour. The findings reveal sophisticated patterns in how users assess information value, integrating practical utility, emotional resonance, and social validation. This dimension emerges as particularly crucial in natural social media interactions, where immediate perceived benefit often drives engagement and sharing behaviour.

Health information adoption behaviour manifests as a dynamic, non-linear process, reflecting the complex nature of health decision-making in social media environments. The analysis reveals how adoption decisions involve multiple stages of evaluation and implementation, with users actively negotiating between different information sources and competing recommendations. Particularly significant is the role of social validation and peer experience in shaping adoption patterns.

These findings provide crucial insights into the natural mechanisms of health information dissemination and adoption within social media environments whilst establishing a robust foundation for subsequent quantitative investigation. The identified dimensions and their interactions suggest the need for more subtle approaches to health communication that account for both the complexity of natural user behaviour and the unique characteristics of social media platforms. Moreover, these findings inform the development of the quantitative research phase by highlighting key variables and relationships requiring systematic examination within the context of authentic social media interaction patterns.

5.4 Triangulation and Integration of Qualitative Findings

This study synthesises and integrates findings from both the interview study and comment analysis. The triangulation process reveals both convergent and complementary insights, contributing to a more comprehensive understanding of health information adoption on social media platforms.

Common Findings

The analysis reveals substantial consistency between the interview study and comment analysis, with both methods identifying six primary categories that influence health information adoption on social media platforms.

Regarding information quality factors, both methods emphasised the critical importance of scientific accuracy and rigour while highlighting the necessity of comprehensive and timely information delivery. The findings consistently demonstrate that users value not only the technical accuracy of health information but also its practical applicability and accessibility in daily life.

In terms of information source factors, both methods revealed the fundamental importance of professional expertise and institutional reputation in establishing credibility. Users consistently demonstrated sophisticated evaluation processes for source reliability, particularly emphasising the importance of transparency regarding potential conflicts of interest. This finding suggests an evolved understanding among social media users of the complex nature of health information sources.

The analysis of information channel factors through both methods highlighted the significant influence of platform-specific characteristics on information dissemination patterns. The findings demonstrate how platform interface design and social interaction features fundamentally shape both information accessibility and user engagement patterns. This understanding proves crucial for developing effective health communication strategies across different social media platforms.

Both methods revealed complex patterns in how recipient factors influence information processing and adoption. Users' individual knowledge levels and personal experiences emerged as crucial elements shaping their ability to evaluate and integrate health information. The findings consistently demonstrate how critical thinking abilities and health literacy levels create distinct patterns of information engagement and understanding.

Perceived usefulness emerged in both analyses as a crucial mediating factor between information characteristics and adoption behaviour. The findings consistently show how users evaluate practical value and personal relevance when assessing health information, with immediate applicability playing a crucial role in determining perceived usefulness.

Finally, both methods revealed health information adoption as a multi-stage process influenced by both individual and social factors. The findings demonstrate how users engage in complex evaluation processes before adoption, with social validation and implementation feasibility playing crucial roles in determining final adoption outcomes.

Differences and Complementarities

While the two methods revealed consistent major themes, they provided distinct and complementary insights that enriched the overall understanding of health information adoption processes. The interview study provided deeper insights into individual decision-making processes and professional evaluation criteria, offering contextual information about how users engage with health information over time. Participants' detailed narratives revealed subtle perspectives on personal barriers and facilitators to information adoption, along with sophisticated strategies for evaluating information credibility.

In contrast, the comment analysis captured spontaneous user reactions and concerns in natural social media environments, revealing important insights about group dynamics and social influence patterns that were less apparent in individual interviews. This method uniquely highlighted cultural and ethical considerations, privacy concerns, and platform-specific interaction patterns that emerge in large-scale, anonymous online environments. The complementarity between these methods enhanced understanding by providing both reflective and immediate perspectives, capturing individual and collective behaviours, and revealing both explicit and implicit factors influencing health information adoption.

Complexity of Recipient Factors

Through comprehensive analysis of both methods, the complexity of recipient factors emerged as a particularly significant finding. This analysis revealed that recipient factors operate through two distinct but interrelated dimensions: knowledge level and cognitive involvement. The knowledge level dimension includes health literacy capabilities, information processing skills, and professional expertise, primarily moderating how users evaluate and understand health information. This dimension fundamentally shapes users' ability to assess scientific validity, evaluate source credibility, and apply information appropriately. Cognitive involvement, as the second dimension, operates through personal interest, emotional engagement, and motivational factors. This dimension primarily moderates the relationship between perceived usefulness and adoption behaviour by influencing information processing depth and implementation commitment. The interaction between these dimensions creates complex patterns of information engagement and adoption behaviour that vary significantly across different user segments and contexts.

Preliminary Theoretical Framework

The integration of findings suggests a theoretical framework incorporating direct, mediating, and moderating effects. Information characteristics appear to directly influence perceived usefulness, which in turn affects health information adoption. The framework suggests that perceived usefulness mediates the relationship between information characteristics and adoption behaviour, while knowledge level and cognitive involvement serve as crucial moderating factors. This preliminary framework provides a robust foundation for developing specific hypotheses and measurement approaches in the quantitative phase of research.

5.5 Implications for Quantitative Study Design

The qualitative findings provide crucial guidance for designing the quantitative phase of research, particularly in terms of variable operationalisation and model development. The findings suggest that information quality, source, and channel characteristics should be measured as distinct constructs, each capturing multiple aspects of information characteristics. Information quality measurement should include scientific accuracy, comprehensiveness, timeliness, and practical relevance, while source measurement should address professional expertise, institutional credibility, and transparency. The operationalisation of channel characteristics should focus on platform features, interface design, and social interaction capabilities that influence information dissemination and engagement. Perceived usefulness emerges as a crucial mediating variable that should be measured through assessments of practical value, personal relevance, and implementation feasibility. The dependent variable, health information adoption, requires measurement approaches that capture both immediate adoption intentions and longer-term engagement patterns.

The findings regarding recipient factors suggest the need for two distinct moderating variables. Knowledge level measurement should include health literacy, technical understanding, and professional background, while cognitive involvement measurement should address personal interest, risk perception, and emotional engagement. This differentiation allows for a more precise examination of how user characteristics influence the health information adoption process.

These insights provide the development of research hypotheses and measurement items. The theoretical framework suggests the need to examine direct effects between information characteristics and perceived usefulness, as well as between perceived usefulness and adoption behaviour. Additionally, the framework indicates the importance of testing mediating effects through perceived usefulness and moderating effects through knowledge level and cognitive involvement.

The careful integration of qualitative findings into quantitative research design enhances the potential for meaningful theoretical contributions and practical implications in understanding health information adoption on social media platforms. This framework provides a systematic foundation for subsequent research phases, including hypothesis development, survey instrument design, and statistical analysis planning.

5.6 Chapter Summary

This chapter presents the process and results of qualitative study through the systematic analysis of interview transcript and social media comments. By triangulating and integrating the findings from these two qualitative methods, six key constructs were identified as influential factors in the health information adoption process on social media platforms: information quality, information source, information channel, recipient factors, perceived usefulness, and health information adoption. The qualitative findings suggest that information quality, information source, and information channel are core factors influencing users' evaluation and perception of health information. Perceived usefulness emerged as a crucial factor directly influencing users' adoption decisions, potentially mediating the relationship between information characteristics and adoption behaviour. Moreover, recipient factors subdivided into the dimensions of knowledge level and cognitive involvement, appeared to play a moderating role in the information processing and decision-making stages of the health information adoption process.

While qualitative research provides insights into the complex dynamics of health information adoption on social media, it is not without limitations. The interview and comment samples, while diverse, may not be entirely representative of all user demographics and health topics. Therefore, in the next chapter, these qualitative findings will be integrated with relevant literature to develop research hypotheses and construct the theoretical model and testing the proposed theoretical framework by conducting a pre-survey.

Chapter 6 Model Development and Hypotheses

6.1 Overview

This chapter develops research hypotheses and constructs a theoretical framework for the quantitative phase of this study, drawing on both the qualitative findings presented in Chapter 5 and relevant literature. The chapter concludes with the development and validation of measurement scales through a pre-survey analysis, culminating in the design of the formal survey questionnaire.

6.2 Development of Research Hypotheses

This study examines the relationships between key constructs in health information adoption on social media platforms. The theoretical framework includes seven latent variables: information quality, information source, information channel, perceived usefulness, health information adoption, level of knowledge, and cognitive involvement. The hypothesised relationships are categorised into direct effects, mediating effects, and moderating effects.

6.2.1 Direct Effect Hypotheses

Information Quality and Perceived Usefulness (H1)

Information quality refers to users' evaluation of health information characteristics on social media platforms. Information quality has been conceptualised through multiple dimensions, originally established by Wang and Strong (1996) as intrinsic, contextual, representational, and accessibility quality. This multidimensional construct is particularly critical in social media health contexts where content varies widely in reliability and undergoes limited formal verification.

The theoretical relationship between information quality and perceived usefulness has been established in several foundational frameworks. The Information Systems Success Model (DeLone and McLean, 2003) suggests information quality affects user satisfaction and system use, though it does not explicitly position perceived usefulness as a mediating mechanism. This theoretical limitation was addressed by Wixom and Todd (2005), who bridged object-based beliefs (information quality) with behavioural beliefs (perceived usefulness) by demonstrating that information satisfaction mediates the relationship between information quality and usefulness perceptions.

Empirical research has consistently supported the influence of information quality on perceived usefulness across various contexts. Sussman and Siegal (2003) found that argument quality directly influences perceived usefulness in their Information Adoption Model. Similarly, Bhattacherjee and Sanford (2006), while not specifically focused on health information, demonstrated that information quality influences perceived usefulness through both central and peripheral routes of information processing.

In health information contexts specifically, Sillence et al. (2007) observed that health information quality factors influenced users' perceptions of information usefulness in their longitudinal study of online health information evaluation. Their research showed that analytical and affective dimensions of quality assessment affected how users determined the utility of health websites for their decision-making process.

The social media environment introduces unique considerations for this relationship. As Metzger and Flanagin (2013) note, digital information environments have transformed how people assess information quality, with users increasingly relying on collaborative and distributed evaluation mechanisms. These altered assessment strategies may influence how quality perceptions translate into usefulness judgments in social media contexts.

Based on these theoretical foundations and empirical evidence:

H1: ***Information quality has a positive influence on perceived usefulness.***

Information Source and Perceived Usefulness (H2)

Information source refers to the perceived credibility, expertise, and trustworthiness of content providers on social media platforms. Source evaluation represents a fundamental component of information processing across communication contexts (Wathen and Burkell, 2002).

The theoretical relationship between source characteristics and perceived usefulness draws primarily from dual-process theories of persuasion. The Elaboration Likelihood Model (Petty and Cacioppo, 1986) suggests that when users process information, source characteristics can influence message evaluation through both central and peripheral routes. When cognitive resources are limited—as often occurs in social media environments with abundant information—users may rely more heavily on source characteristics as heuristic cues when forming utility judgments.

Empirical support for this relationship comes from studies on information adoption in online environments. Sussman and Siegal (2003) demonstrated that source credibility significantly influences perceived usefulness in electronic communication contexts. Their findings suggest that users incorporate source evaluations when determining information utility, especially when dealing with complex or ambiguous information.

In health information contexts, source credibility takes on particular importance due to potential health consequences of misinformation. Sillence et al. (2007) found that users evaluate health website credibility based on source factors, with these assessments influencing subsequent information use decisions. Their research revealed that source trust operates as a primary filter in health information evaluation processes.

Social media platforms create unique challenges for source assessment. Unlike traditional health information sources with clear institutional affiliations, social media content creators span a spectrum from healthcare organisations to individual users sharing personal experiences (Fritch and Cromwell, 2001). This diversity requires users to employ different evaluation strategies when determining information utility.

While traditional source credibility theory focuses on expertise and trustworthiness dimensions (Hovland et al., 1953), social media environments introduce additional factors such as homophily, social validation, and consistency that influence how source characteristics affect perceived usefulness (Metzger et al., 2010). This expanded conceptualisation acknowledges the networked nature of social media communication where credibility assessments extend beyond individual sources to include social endorsements.

Based on these theoretical foundations and empirical evidence:

H2: ***Information source has a positive influence on perceived usefulness.***

Information Channel and Perceived Usefulness (H3)

Information channel refers to the technological and functional features of social media platforms that facilitate health information dissemination and consumption. The theoretical foundation for examining channel influence on perceived usefulness draws primarily from media theories that explain how communication channel capabilities affect information processing.

Media Synchronicity Theory (Dennis et al., 2008) provides a theoretical basis for understanding how channel characteristics influence communication effectiveness. The theory proposes that communication performance depends on the match between the media capabilities and the communication processes required for a task. Five key capabilities—transmission velocity, parallelism, symbol sets, rehearsability, and reprocessability—determine a channel's synchronicity and its suitability for different communication processes.

Social media platforms introduce distinctive affordances that influence how users process and evaluate information. Treem and Leonardi (2013) identify visibility, editability, persistence, and association as key affordances that shape information exchange and user perceptions in social media contexts. These affordances can directly influence how users perceive information usefulness by affecting information accessibility, presentation, and social context.

Channel characteristics may influence perceived usefulness through multiple mechanisms. First, they can affect information processing ease. As proposed by the Technology Acceptance Model (Davis, 1989), perceived ease of use, which is partly determined by channel characteristics, can influence perceived usefulness. Second, channel features can provide contextual cues that assist users in evaluating information relevance and applicability. Third, interactive channel features can enhance information richness through user comments, ratings, and social validation indicators, potentially influencing perceived usefulness (Rice, 1992).

In health information contexts specifically, channel characteristics take on additional importance. Lu et al. (2005) demonstrated that channel features affected perceived usefulness in mobile technology adoption, while Fox and Duggan (2013) found that platform characteristics affected how users engaged with and perceived health information across different digital channels.

While traditional media theories provide valuable insights, social media environments introduce complexities not fully captured in these frameworks. The simultaneous presence of multiple communication modes, algorithmic content distribution, and networked information exchange create a more complex information environment than what was originally considered in media synchronicity or richness theories.

Based on these theoretical foundations and empirical evidence:

H3: ***Information channel has a positive influence on perceived usefulness.***

Perceived Usefulness and Health Information Adoption (H4)

Perceived usefulness represents users' belief that specific information will enhance their health-related decision-making or knowledge. The theoretical foundation for examining the relationship between perceived usefulness and adoption behaviour stems primarily from the Technology Acceptance Model (Davis, 1989), which establishes perceived usefulness as a fundamental determinant of user acceptance and usage behaviour.

The theoretical significance of perceived usefulness has been further validated through the Unified Theory of Acceptance and Use of Technology (Venkatesh et al., 2003). This comprehensive model synthesises eight prominent technology acceptance theories, confirming that performance expectancy serves as the strongest predictor of behavioural intention across different contexts and user populations.

In information adoption contexts specifically, Sussman and Siegal's (2003) Information Adoption Model positions perceived usefulness as the direct antecedent to information adoption. Their model, integrating elements from technology acceptance and persuasion theories, provides a theoretical framework for understanding how perceptions of information utility translate into adoption decisions in computer-mediated environments.

Research in health information contexts has demonstrated the critical role of perceived usefulness in driving adoption behaviours. Ahadzadeh et al. (2015) found that perceived usefulness significantly predicted health-related internet use intentions, demonstrating the importance of utility perceptions in health information adoption. Similarly, Or and Karsh (2009), in their systematic review of patient acceptance of consumer health information technology, identified perceived usefulness as one of the most consistent predictors of adoption across multiple studies.

Based on these theoretical foundations and empirical evidence:

H4: *Perceived usefulness has a positive influence on health information adoption.*

6.2.2 Mediation Effect Hypotheses

Information Quality's Indirect Influence Through Perceived Usefulness (H5)

The mediating role of perceived usefulness in the relationship between information quality and adoption is theoretically grounded in information systems success theory and technology acceptance research. This mediation mechanism represents a critical pathway through which information characteristics influence user behaviour in digital environments.

DeLone and McLean's (2003) Information Systems Success Model provides a foundational framework suggesting that system and information characteristics influence use and net benefits through intermediate perceptual constructs. While their original model does not explicitly position perceived usefulness as a mediating mechanism, subsequent adaptations and extensions have incorporated this pathway. Petter and McLean's (2009) meta-analysis of studies applying the Information Systems Success Model found support for indirect effects of information quality on system use, suggesting the presence of mediating mechanisms similar to perceived usefulness.

Wixom and Todd (2005) offer more direct theoretical support for this mediation effect through their integrated model of user satisfaction and technology acceptance. Their research demonstrates how object-based beliefs (such as information quality) influence behavioural outcomes through behavioural beliefs (such as perceived usefulness). This integration of satisfaction and acceptance perspectives provides a theoretical basis for examining perceived usefulness as a mediator in information adoption processes.

In the context of online information evaluation, Sussman and Siegal's (2003) Information Adoption Model positions perceived usefulness as the direct antecedent to information adoption, with information quality (operationalised as argument quality) influencing adoption through this mediating pathway. Their empirical validation demonstrated that perceived usefulness fully mediates the relationship between argument quality and information adoption in electronic communication contexts.

Bhattacherjee and Sanford (2006) extend this understanding by applying the Elaboration Likelihood Model to examine influence processes in IT acceptance. Their research reveals that information characteristics affect adoption behaviours primarily through their impact on users' cognitive assessments of information utility, providing further theoretical support for the mediating role of perceived usefulness.

In health information contexts, Eysenbach (2007) proposed that quality and credibility assessments influence health information use through intermediate evaluative processes that determine the information's utility for health-related needs. Eysenbach's framework of 'apomediaries' suggests that online health information quality affects adoption through its impact on perceived relevance and usefulness.

Based on these theoretical foundations and empirical evidence:
H5: ***Information quality indirectly influences health information adoption through the mediating role of perceived usefulness.***

Information Source's Indirect Influence Through Perceived Usefulness (H6)

The mediating role of perceived usefulness in the relationship between source characteristics and information adoption is supported by multiple theoretical frameworks in information processing and adoption research. This mediation effect represents an important mechanism through which source evaluations influence user behaviour in digital environments.

The theoretical foundation for this mediation effect draws from the Information Adoption Model (Sussman and Siegal, 2003), which establishes relationships between source credibility, perceived usefulness, and information adoption. Their model, empirically validated in electronic communication contexts, demonstrates that source credibility influences adoption behaviour primarily through its effect on perceived usefulness. This mediation pathway suggests that users' evaluations of source characteristics affect adoption decisions by influencing their perceptions of information utility.

Dual-process theories of persuasion provide additional theoretical support for this mediation effect. The Elaboration Likelihood Model (Petty and Cacioppo, 1986) suggests that when processing persuasive messages, source characteristics can influence attitudes and behaviours through central or peripheral routes. While the model does not explicitly include perceived usefulness, its conceptualisation of cognitive responses as mediating mechanisms between message characteristics and persuasion outcomes parallels the mediating role of perceived usefulness in information adoption.

Empirical support for this mediation effect comes from studies across various information contexts. Bhattacherjee and Sanford (2006) found that source credibility influenced IT acceptance attitudes through perceived usefulness, with this indirect effect operating primarily through peripheral processing routes. Although their study focused on IT acceptance rather than health information adoption, the identified mediating mechanism provides relevant insights for understanding how source evaluations influence adoption behaviour.

In health information contexts specifically, source credibility takes on heightened importance due to potential health consequences of misinformation. Hu and Sundar (2010) found that the influence of source credibility on health website evaluation was mediated by users' perceptions of the information's utility for health decision-making. Their experimental study examining how users evaluate health information from different online sources provides empirical support for the mediating role of perceived usefulness in the relationship between source credibility and behavioural intentions.

Based on these theoretical foundations and empirical evidence:

H6: *Information source indirectly influences health information adoption through the mediating role of perceived usefulness.*

Information Channel's Indirect Influence Through Perceived Usefulness (H7)

The mediating role of perceived usefulness in the relationship between channel characteristics and information adoption is theoretically supported by research in media capabilities and information processing. This mediation effect represents a key mechanism through which channel features influence user behaviour in digital environments.

Media Synchronicity Theory (Dennis et al., 2008) provides a theoretical foundation for understanding how channel capabilities influence communication processes and outcomes. The theory suggests that media capabilities affect communication performance by influencing information processing and transmission. While the theory does not explicitly include perceived usefulness as a mediating construct, its focus on how media capabilities affect communication effectiveness parallels the mediating role of perceived usefulness in the channel-adoption relationship.

Technology Acceptance Model research offers more direct support for this mediation pathway. Davis (1989) established that system characteristics influence usage behaviour through perceived usefulness, with subsequent research extending this framework to various technological contexts. Lee et al.'s (2003) meta-analysis of TAM studies confirmed the mediating role of perceived usefulness across diverse technology applications, supporting its potential application to channel-adoption relationships in social media contexts.

Empirical research has provided support for the mediating role of perceived usefulness between channel characteristics and usage behaviour. Lu et al. (2005) found that mobile commerce channel features influenced adoption intentions primarily through perceived usefulness, demonstrating the importance of this mediation pathway in explaining how channel characteristics affect user behaviour.

In the context of social media specifically, channel affordances may influence information adoption through their effect on perceived usefulness. Treem and Leonardi (2013) identified visibility, editability, persistence, and association as key social media affordances that shape how users interact with and evaluate information. These affordances may influence adoption behaviour by affecting how users perceive the utility of information for their health-related needs.

In health communication contexts, Tao (2009) demonstrated that characteristics of internet-based communication channels influenced health information seeking behaviour through their impact on perceived information utility. This research provides empirical support for the proposition that channel features affect adoption behaviour by influencing perceptions of information usefulness.

Based on these theoretical foundations and empirical evidence:

H7: ***Information channel indirectly influences health information adoption through the mediating role of perceived usefulness.***

6.2.3 Moderation Effect Hypotheses

Knowledge Level's Moderating Effects (H8a, H8b, H8c)

The moderating role of knowledge level in information processing relationships is theoretically grounded in established frameworks of information processing and cognitive psychology. Knowledge level, defined as the extent of domain-specific expertise or familiarity a user possesses, fundamentally shapes how individuals process and evaluate information.

The Elaboration Likelihood Model (Petty and Cacioppo, 1986) provides a foundational theoretical framework for understanding this moderation effect. ELM proposes that individuals' motivation and ability to process information determine which processing route they employ when evaluating messages. Knowledge level, as a component of processing ability, influences users' capacity to engage in systematic evaluation of information characteristics. This theoretical perspective suggests that users with different levels of health knowledge will evaluate information quality, source credibility, and channel characteristics differently when determining information usefulness.

Chaiken's (1980) Heuristic-Systematic Model offers additional theoretical support for this moderation effect. The model proposes that individuals engage in systematic processing when they possess both the motivation and cognitive capacity to carefully evaluate message content. Knowledge level, as a key determinant of cognitive capacity, influences the extent to which users can systematically evaluate information characteristics rather than relying on heuristic processing strategies. However, the model acknowledges that even knowledgeable individuals may resort to heuristic processing under conditions of limited cognitive resources or time constraints, conditions often present in social media environments.

Empirical research has demonstrated the moderating effect of knowledge level across various information processing contexts. In the domain of health information specifically, Dutta-Bergman (2004) found that health knowledge levels significantly influenced how individuals processed and evaluated health information, with different patterns of information seeking and assessment observed across knowledge groups. This research supports the theoretical proposition that knowledge level fundamentally alters how users process and respond to health information characteristics.

For information quality assessments, knowledge level plays a particularly important moderating role. Grewal et al. (1994) demonstrated that domain knowledge moderated the relationship between argument quality and message evaluation, with high-knowledge individuals showing greater sensitivity to quality variations. This finding suggests that health knowledge may enhance users' ability to discern quality differences in health information on social media, potentially strengthening the relationship between information quality and perceived usefulness.

Regarding source evaluation, prior research indicates that knowledge level influences how individuals respond to source characteristics. Winter and Krämer (2012) found that domain expertise moderated the influence of source credibility on information evaluation, with different patterns observed for experts versus novices. This research suggests that health knowledge may alter how users incorporate source evaluations into their usefulness judgments on social media.

For channel characteristics, knowledge level may similarly moderate how users respond to media features. Spence and Moinpour (1972) found that expertise moderated individuals' responses to communication channel characteristics, with different effects observed across knowledge levels. In the social media context, this suggests that health knowledge may influence how channel affordances affect users' perceptions of information usefulness.

Based on these theoretical foundations and empirical evidence:

H8a: ***The level of knowledge moderates the relationship between information quality and perceived usefulness.***

H8b: ***The level of knowledge moderates the relationship between information source and perceived usefulness.***

H8c: ***The level of knowledge moderates the relationship between information channel and perceived usefulness.***

Cognitive Involvement's Moderating Effect (H9)

The moderating role of cognitive involvement in the relationship between perceived usefulness and adoption behaviour is theoretically supported by research in information processing and engagement. Cognitive involvement, defined as the extent to which an individual is mentally engaged with and actively processing information, represents a key psychological state that influences how perceptions translate into behaviour.

The Elaboration Likelihood Model (Petty and Cacioppo, 1986) provides a theoretical foundation for understanding this moderation effect. ELM suggests that higher involvement leads to more elaborative processing of message arguments and stronger attitude-behaviour consistency. When applied to the usefulness-adoption relationship, this theory suggests that higher cognitive involvement should strengthen the link between perceived usefulness and adoption decisions by enhancing users' thoughtful consideration of information utility.

Zaichkowsky's (1985) conceptualisation of involvement as personal relevance provides additional theoretical support for this moderation effect. Her research establishes involvement as a key factor influencing how individuals process information and form behavioural intentions. When applied to health information contexts, this suggests that users who are more cognitively involved will show stronger connections between their usefulness perceptions and subsequent adoption behaviour.

Empirical research has demonstrated the moderating effect of involvement across various behavioural contexts. Celsi and Olson (1988) found that involvement moderated the relationship between cognitive elaboration and memory for product information, with higher involvement strengthening this relationship. In technology acceptance research, Bhattacherjee and Sanford (2006) demonstrated that job relevance (a concept related to involvement) moderated the influence of perceived usefulness on IT acceptance attitudes, providing empirical support for involvement's moderating role.

In health information contexts specifically, involvement takes on particular importance due to the personal relevance of health decisions. Park and Lee (2008) found that involvement with health issues moderated consumers' responses to online health information, with higher involvement strengthening the relationship between evaluative judgments and behavioural intentions. This research supports the theoretical proposition that cognitive involvement enhances the translation of perceived usefulness into adoption behaviour.

Based on these theoretical foundations and empirical evidence:

H9: ***Cognitive involvement moderates the relationship between perceived usefulness and health information adoption.***

6.3 Theoretical Framework

This study proposes a comprehensive theoretical framework as shown in Figure 6.1 that examines the adoption mechanisms of health-related information in social media environments. The framework integrates core concepts from the Information Adoption Model and the Technology Acceptance Model, while addressing the unique characteristics of social media platforms and health information contexts.

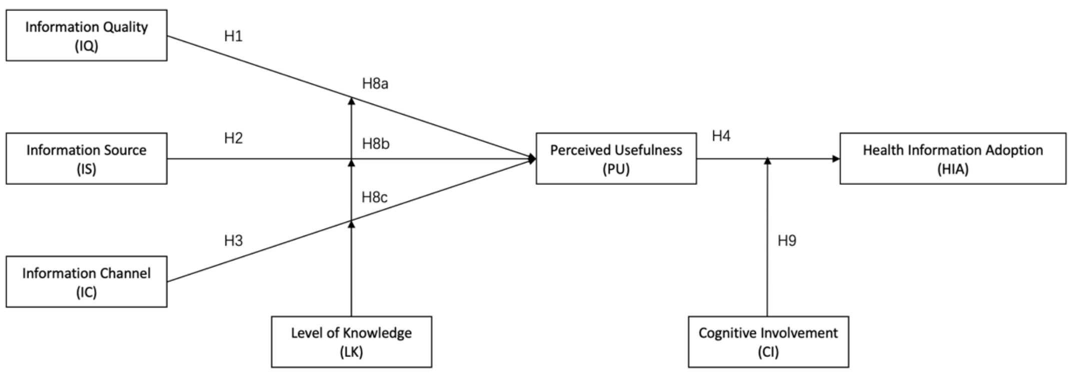

Figure 6.1: Theoretical Framework

The framework consists of seven latent constructs that interact to explain how users evaluate and adopt health information on social media platforms. At its core, the framework posits that information characteristics influence adoption behaviour through cognitive evaluation processes, with these relationships moderated by individual user characteristics.

The three exogenous variables—Information Quality, Information Source, and Information Channel—represent fundamental characteristics influencing users' health information evaluation on social media:

Information Quality reflects users' overall assessment of the information's merit. In social media health contexts, quality assessment takes on particular importance given the absence of traditional gatekeeping mechanisms and the potential health consequences of misinformation.

Information Source captures the perceived credibility and expertise of content providers. The construct encompasses traditional dimensions of expertise and trustworthiness while acknowledging how social media environments introduce additional credibility indicators such as social endorsement and consistency.

Information Channel represents the technological and functional features of social media platforms that facilitate health information dissemination. These channel characteristics fundamentally shape how users encounter and process health information in social media environments.

Perceived Usefulness serves as the central mediating mechanism in the framework, bridging the gap between information characteristics and adoption behaviour. In social media environments, perceived usefulness represents users' cognitive assessment of information utility for their health-related needs, a critical evaluation that precedes adoption decisions.

Health Information Adoption represents the dependent variable in the framework, capturing users' acceptance and utilisation of health information encountered on social media platforms. This construct encompasses both cognitive (belief integration) and behavioural (information application) dimensions of adoption.

The framework introduces two moderating variables that account for individual differences in information processing capabilities and motivation:

Level of Knowledge moderates the relationships between the exogenous variables and Perceived Usefulness, reflecting how users' prior health domain knowledge influences their information evaluation processes.

Cognitive Involvement moderates the relationship between Perceived Usefulness and Health Information Adoption, capturing how users' psychological engagement affects the translation of utility perceptions into adoption decisions.

The framework represents a synthesis of information adoption research adapted to the specific context of health information on social media platforms. By incorporating both traditional information evaluation constructs (quality and source) and the novel addition of channel characteristics, the model provides a comprehensive representation of the factors influencing health information adoption in contemporary digital environments. The inclusion of moderating variables further enhances the model's explanatory power by accounting for individual differences in information processing and engagement.

As shown in Figure 6.1, the relationships between constructs represent the previously developed hypotheses. The direct effects (H1-H4) establish the primary pathways through which information characteristics influence adoption behaviour. The mediating effects (H5-H7) articulate the mechanism by which information characteristics indirectly influence adoption through perceived usefulness. The moderating effects (H8a-H8c, H9) identify boundary conditions that qualify these relationships across different user groups and contexts.

This theoretical framework guides the empirical investigation in subsequent chapters, providing a structured approach to examining how users evaluate and adopt health information on social media platforms. The model's integration of information characteristics, cognitive evaluation processes, and individual difference factors offers a multidimensional perspective on health information adoption that acknowledges the complexity of this phenomenon in social media environments.

6.4 Measurement Development

The development of measurement instruments for this study integrated established scales from literature with qualitative insights derived from Chapter 5, following a systematic mixed-method approach. This methodologically robust approach led to the identification and operationalisation of seven key latent variables: Information Quality, Information Source, Information Channel, Perceived Usefulness, Health Information Adoption, Level of Knowledge, and Cognitive Involvement. Each construct was carefully developed to ensure both theoretical validity and contextual relevance for the social media health information environment.

The Information Quality construct was operationalised through 15 carefully designed measurement items, drawing from DeLone and McLean’s (2003) Information Systems Success Model and Wang and Strong’s (1996) data quality framework while incorporating insights from the qualitative findings. These items systematically assess fifteen distinct dimensions of information quality: consistency (logical coherence), accuracy (precision of information), completeness (comprehensive coverage), adequacy (appropriate amount), verifiability (source verification), objectivity (unbiased presentation), reliability (trustworthiness), relevance (applicability to needs), usefulness (practical value), operability (actionable suggestions), timeliness (current information), understandability (clarity of expression), accessibility (ease of comprehension), interestingness (engagement level), and attractiveness (appeal of presentation).

The Information Source construct comprises 5 dimensions identified through both literature review (Ohanian, 1990; Bhattacherjee and Sanford, 2006) and qualitative findings. These dimensions measure expertise (professional knowledge), authoritativeness (position of authority), reliability (trustworthiness), affinity (approachability), and transparency (clear identity and background). The qualitative findings particularly emphasised the importance of source transparency and affinity in the social media context, leading to the inclusion of these specific items.

The Information Channel construct, comprising 8 items, was developed by synthesising Media Synchronicity Theory (Dennis et al., 2008) with findings from social media research (Lin and Lu, 2011) and insights from the qualitative study. The items evaluate professionalism (platform expertise), accessibility (user-friendliness), interactivity (user engagement), reliability (platform trustworthiness), functionality (personalised features), dependency (usage frequency), sociability (social influence), and profitability (commercial balance). The inclusion of sociability and profitability dimensions specifically emerged from the qualitative findings, reflecting the unique characteristics of health information dissemination on social media platforms.

All 42 measurement items employ a seven-point Likert scale (1 = Strongly Disagree to 7 = Strongly Agree), providing sufficient granularity to capture subtle responses while maintaining participant comprehension. This scale choice aligns with established practice in social science research (DeVellis, 2016) and was validated through the qualitative phase of the study. Table 6.1 presents the complete measurement instrument, demonstrating the systematic correspondence between theoretical dimensions and operational items. Each measurement item was carefully worded to ensure clarity for non-native English speakers while maintaining theoretical precision.

Construct	Measurement Items		Sources
Information Quality (IQ)	IQ1	This health information is coherent and logical in its content.	DeLone and McLean (2003); Wang and Strong (1996)
	IQ2	The descriptions in this health information are accurate.	
	IQ3	This health information is comprehensive and complete in its content.	
	IQ4	The amount of information provided is appropriate, neither excessive nor lacking.	
	IQ5	The source of this health information is verifiable.	
	IQ6	This health information is objective and impartial.	
	IQ7	The content of this health information is trustworthy.	
	IQ8	This health information is relevant to my needs.	
	IQ9	This health information is useful to me.	
	IQ10	This health information provides feasible suggestions.	
	IQ11	This health information is novel and timely in its content.	
	IQ12	The language used in this health information is straightforward and easy to understand.	
	IQ13	The presentation of this health information is user-friendly and readable.	
	IQ14	The content of this health information is interesting and engaging.	
	IQ15	The presentation format of this health information is appealing.	
Information Source (IS)	IS1	The disseminator of this information is an expert in the medical and health field.	Bhattacherjee and Sanford (2006); Ohanian (1990)
	IS2	The disseminator of this information holds an authoritative position in the health domain.	
	IS3	The disseminator of this information is trustworthy.	
	IS4	The disseminator of this information comes across as approachable and amiable.	
	IS5	The identity and background of the disseminator of this information are transparent.	
Information Channel (IC)	IC1	The interface design of this social media platform is professional.	Dennis et al. (2008); Lin and Lu (2011)
	IC2	This platform is user-friendly and provides a good overall experience.	
	IC3	This platform supports user interaction and participation.	
	IC4	This platform is trustworthy and prioritises user privacy protection.	
	IC5	The personalised recommendation algorithms and overall user experience of this platform are excellent.	
	IC6	I frequently use this platform to obtain health information.	

	IC7	The comments and interactions of other users on this platform also influence my adoption of health information.	
	IC8	This platform is commercially operated in moderation, without compromising its credibility.	
Perceived Usefulness (PU)	PU1	This health information provides me with expert knowledge about health conditions.	Davis (1989); Bhattacherjee and Sanford (2006)
	PU2	This health information is helpful in answering my health-related questions.	
	PU3	This health information is helpful for improving my health condition.	
	PU4	This health information is valuable for my health-related decisions.	
Health Information Adoption (HIA)	HIA1	I will endorse this health information (e.g., like, upvote).	Sussman and Siegal (2003); Zhang et al. (2017)
	HIA2	I will share this health information with others (e.g., share, retweet).	
	HIA3	I will adjust my health behaviours based on this information.	
	HIA4	I will follow this information's suggestions in my health management.	
Level of Knowledge (LK)	LK1	I have good knowledge about this health topic.	Alba and Hutchinson (1987); Park et al. (1994)
	LK2	I am familiar with this health information topic.	
	LK3	I am expertise with this health topic.	
Cognitive Involvement (CI)	CI1	I am deeply engaged with this health information.	Zaichkowsky (1985, 1994)
	CI2	I put considerable mental effort into processing this health information.	
	CI3	This health information captures my attention and stimulates my thinking.	

Table 6.1: Measurement Items and Sources

6.5 Pre-Survey

Before finalising the formal survey questionnaire, a pre-survey was conducted to evaluate and refine the initial measurement instrument. This essential validation phase was designed to assess the reliability and validity of the measurement items whilst ensuring their comprehensibility and practical applicability. The pre-survey involved 120 participants recruited through the WJX, with data collection facilitated through QR code distribution methods to enable convenient access via both mobile devices and computers.

6.5.1 Reliability Analysis

The reliability analysis revealed exceptional internal consistency across all measurement scales. As shown in Table 6.2, Cronbach's alpha coefficients ranged from 0.843 to 0.961 for individual constructs, with an overall scale reliability of 0.953, demonstrating excellent reliability across all measurement scales. The 'alpha if item deleted' statistics indicated that all items contributed meaningfully to their respective scales, with no substantial improvements in reliability possible through item removal. These results supported the retention of all measurement items for the main study.

Construct	Cronbach's α	N of Items	Measurement Items	Cronbach's α if Item Deleted
Information Quality (IQ)	0.958	15	IQ1	0.956
			IQ2	0.955
			IQ3	0.956
			IQ4	0.956
			IQ5	0.954
			IQ6	0.955
			IQ7	0.954
			IQ8	0.955
			IQ9	0.956
			IQ10	0.957
			IQ11	0.954
			IQ12	0.955
			IQ13	0.956
			IQ14	0.955
			IQ15	0.954
Information Source (IS)	0.907	5	IS1	0.884
			IS2	0.881
			IS3	0.881
			IS4	0.897
			IS5	0.888
Information Channel (IC)	0.947	8	IC1	0.937
			IC2	0.937
			IC3	0.939
			IC4	0.937
			IC5	0.939
			IC6	0.941
			IC7	0.940
			IC8	0.945
Perceived Usefulness (PU)	0.961	4	PU1	0.952
			PU2	0.950
			PU3	0.954
			PU4	0.940
Health Information Adoption (HIA)	0.928	4	HIA1	0.899
			HIA2	0.906
			HIA3	0.917
			HIA4	0.901
Level of Knowledge (LK)	0.891	3	LK1	0.847
			LK2	0.837
			LK3	0.850
Cognitive Involvement (CI)	0.843	3	CI1	0.755
			CI2	0.787
			CI3	0.802
Total Variables	0.953	42	-	-

Table 6.2: The Results of Reliability Analysis

6.5.2 Validity Analysis

The validity assessment began with preliminary tests to examine data suitability for factor analysis. As presented in Table 6.3, the Kaiser-Meyer-Olkin (KMO) measure yielded a value of 0.875, substantially exceeding the recommended threshold of 0.60, whilst Bartlett's test of sphericity produced significant results ($\chi^2 = 4954.768$, $df = 861$, $p < 0.001$), confirming appropriate inter-item correlations for factor analysis (Kaiser, 1974).

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.875
Bartlett's Test of Sphericity	Approx. Chi-Square	4954.768
	df	861
	Sig.	<.001

Table 6.3: KMO and Bartlett's Test

The Exploratory Factor Analysis (EFA), employing principal component analysis with varimax rotation, revealed a seven-factor solution explaining 77.116% of the total variance (Hair et al., 2018). Appendix II-A (Total Variance Explained) shows that the eigenvalues for all seven factors exceeded 1.0, supporting the seven-factor solution. The scree plot (Figure 6.2) further confirmed this solution, showing a clear elbow at the seventh factor. The rotated factor matrix, presented in Appendix II-B (Rotated Component Matrix), converged in eight iterations and demonstrated clear and interpretable factor structures (Costello and Osborne, 2005). Factor loadings for most constructs ranged from 0.661 to 0.887, indicating strong construct validity (Fabrigar and Wegener, 2012).

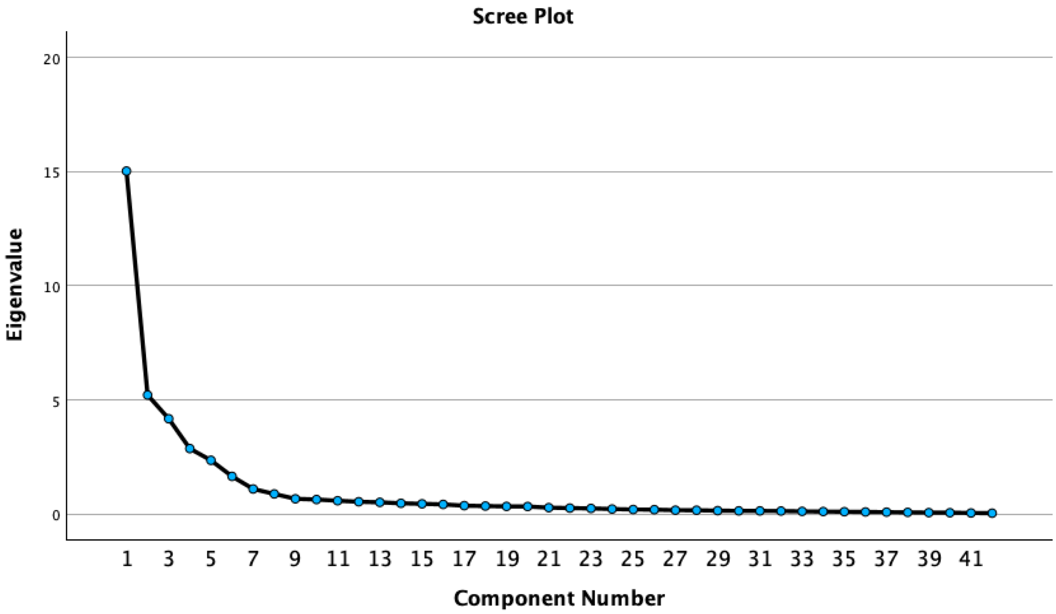

Figure 6.2: Scree Plot

A noteworthy observation emerged regarding the Level of Knowledge (LK) and Cognitive Involvement (CI) constructs. Unlike the other five latent variables, which loaded distinctly on separate factors, as shown in Appendix II-B, the measurement items for LK and CI showed relatively high loadings on the same factor. This pattern likely emerged from the pre-survey questionnaire design, where these items were grouped under the general concept of 'self-perception'. Although LK and CI represent theoretically distinct variables, their measurement items both assess self-perceived aspects—knowledge levels and cognitive involvement, respectively. This conceptual proximity in self-assessment may have influenced participants' differentiation between these constructs during the response process.

Based on these comprehensive findings, several refinements were implemented for the main study questionnaire. The most significant modification involved the strategic separation of LK and CI measurement items into different modules, enhancing their distinction as independent variables. Additional adjustments included optimising item wording to strengthen content validity while maintaining theoretical precision. These refinements aimed to achieve higher factor loadings on corresponding common factors, thereby enhancing construct validity while preserving the theoretical integrity of the measurement model. The pre-survey thus fulfilled its methodological purpose while identifying opportunities for enhancement.

6.6 Chapter Summary

This chapter through a comprehensive review of existing literature and combined with qualitative study findings, 11 research hypotheses were proposed, constructing a complete theoretical framework. This framework describes the relationships between key factors such as Information Quality, Information Source, Information Channel, Perceived Usefulness, Level of Knowledge, Cognitive Involvement, and health information adoption by social media users. This chapter designed a preliminary scale including measurement items for each of the above latent variables. Then, a pre-survey was conducted to analyse the reliability and validity of the preliminary scale. Reliability analysis results show that the measurement items of each latent variable have good internal consistency, with Cronbach's coefficients all above 0.843. In addition, Exploratory Factor Analysis results have found that, except for some cross-loadings between the measurement items of Level of Knowledge and Cognitive Involvement, the remaining measurement items have high loadings on corresponding common factors, preliminarily demonstrating good construct validity.

Based on pre-survey feedback, the formal survey questionnaire has been optimised. This includes dispersing the measurement items of Level of Knowledge and Cognitive Involvement in different modules and modifying some statement expressions to enhance the distinction between these two variables. The final formal survey questionnaire (see Appendix III) evaluates key factors influencing social media users' adoption of health-related information.

The next chapter will present the results of the main survey, employing statistical techniques to rigorously test the proposed theoretical framework and its associated hypotheses.

Chapter 7 Quantitative Results

7.1 Overview

This chapter examines the influencing factors and mechanisms of health-related information adoption on social media through quantitative study. Firstly, descriptive statistical analysis of the sample's demographic characteristics is conducted, and normality tests are performed on the research variables. Secondly, the reliability and validity of the measurement model are assessed through reliability analysis and Confirmatory Factor Analysis (CFA). Subsequently, Structural Equation Modelling is used to examine the overall fit of the theoretical model and the direct relationships between variables. Finally, path analysis is employed to explore mediating and moderating effects.

7.2 Descriptive Statistical Analysis

This study analyses data collected from 500 valid participants through major Chinese social media platforms (WeChat, Douyin, and Weibo), using simple random and snowball sampling techniques, examining both demographic characteristics and measurement properties.

7.2.1 Demographic Analysis

Table 7.1 summarises the demographic characteristics of participants. Regarding gender distribution, there are 217 male participants, accounting for 43.4%, and 283 female participants, accounting for 56.6%. Females slightly outnumber males, but the gender ratio is essentially balanced. This distribution reflects the general characteristics of social media users, providing a relatively balanced gender perspective for the study.

	Frequency	Percent (%)
Gender		
Male	217	43.4
Female	283	56.6
Age		
Between 18 and 25 years	226	45.2
Between 26 and 35 years	138	27.6
Between 36 and 45 years	68	13.6
Between 46 and 55 years	36	7.2
Above 56 years	32	6.4
Qualifications		
Doctor degree	19	3.8
Master degree	89	17.8
Bachelor degree	268	53.6
Diploma certificate	78	15.6
High school certificate	38	7.6
No certificate	8	1.6
Do you have background knowledge in medicine (including current/former medical-related occupations or current/former medical specialisation)?		
Yes	194	38.8
No	306	61.2
Do you regularly read/access/follow health information via social media?		
Yes	371	74.2
No	129	25.8

Table 7.1: Demographics of the Sample (n=500)

The age distribution shows a typical stepwise downward trend. The 18-25 age group has the most participants, accounting for 45.2%, followed by the 26-35 age group at 27.6%; the 36-45 age group at 13.6%; the 46-55 age group at 7.2%; and the 56 and above age group has the least, accounting for only 6.4%. The sample is predominantly composed of young and middle-aged populations, which is highly consistent with the actual user characteristics of social media. This distribution is beneficial for capturing the health information behaviour of the main social media user groups but also indicates potential limitations in studying the elderly population.

Regarding education level, participants with bachelor's degrees are the most numerous, totalling 268 people and accounting for 53.6%, followed by 89 people with master's degrees, accounting for 17.8%; 78 people with college diplomas, accounting for 15.6%; 38 people with high school education, accounting for 7.6%; 19 people with doctoral degrees, accounting for 3.8%; and those with no formal education are the least, only eight people, accounting for 1.6%. Overall, the participants have a relatively high education level, which not only helps improve the quality of the survey data but also provides a good foundation for exploring the impact of education level on health information processing capabilities.

Additionally, 194 participants (38.8%) indicate they have medical-related background knowledge, including current or past work in medical-related fields or relevant academic majors, while 306 participants (61.2%) do not have medical background knowledge. Medical background can have a certain influence on the understanding and judgment of health-related information, and the sample includes both groups, providing possibilities for comparative analysis.

Notably, as high as 74.2% of participants state they regularly obtain health-related information through social media, while only 25.8% do not. This distribution reflects the current important position of social media in health information dissemination, highlighting the practical significance and urgency of studying health information adoption on social media.

Whilst the sample demographics provide an appropriate representation of active social media users, it is important to acknowledge certain limitations in representativeness when compared to China's overall population. The significantly higher proportion of younger participants (45.2% aged 18-25) and those with higher education (75.2% with bachelor's degrees or higher) represents a substantial deviation from China's general population distribution. This demographic skew means that the study results primarily reflect the health information adoption patterns of younger, educated, digitally engaged Chinese citizens rather than the entire population.

The underrepresentation of older age groups (only 13.6% aged over 45) is particularly significant given that older populations often have greater healthcare needs and potentially different information-seeking behaviours. Additionally, the high proportion of educated participants may influence the observed patterns of information evaluation and adoption, as education level likely affects both digital literacy and health literacy. These demographic limitations should be considered when interpreting the findings and their generalisability to the broader Chinese population. Future research would benefit from targeted sampling strategies to better capture the perspectives of older and less educated social media users.

7.2.2 Normality Test

To establish the validity of subsequent statistical analyses, normality tests were performed on all measurement items, with results presented in Table 7.2. According to widely accepted statistical guidelines (Kline, 2011), data can be considered normally distributed when absolute values of skewness are less than 3 and kurtosis values are less than 8. The analysis reveals that all items demonstrate good normality, with skewness values ranging from -0.920 to -0.169 and kurtosis values between -0.924 and 0.477, well within these established thresholds.

Examination of construct-level measurements reveals several noteworthy patterns. The Information Quality construct (M=5.059, SD=1.162) shows consistently positive evaluations across items, suggesting that participants generally perceive health information on social media as being of acceptable quality. The Perceived Usefulness construct (M=4.843, SD=1.444) exhibits relatively higher variance, indicating diverse perspectives on the utility of social media health information. The Cognitive Involvement construct demonstrates the highest mean score (M=5.249, SD=1.197), indicating substantial cognitive engagement when processing health information on social media. The Level of Knowledge construct (M=5.167, SD=1.212) shows consistent responses across items, suggesting stable self-assessments of health information comprehension abilities. The measurement data satisfies the normality assumptions required for subsequent analyses.

Construct	Item	Mean	Std. Deviation	Skewness	Kurtosis	Construct's Mean	Construct's Std. Deviation
Information Quality (IQ)	IQ1	5.070	1.445	-0.920	0.477	5.059	1.162
	IQ2	5.210	1.394	-0.773	-0.096		
	IQ3	5.150	1.411	-0.529	-0.457		
	IQ4	5.070	1.363	-0.406	-0.530		
	IQ5	5.090	1.433	-0.475	-0.579		
	IQ6	5.010	1.434	-0.489	-0.500		
	IQ7	5.150	1.343	-0.487	-0.604		
	IQ8	5.230	1.286	-0.519	-0.358		
	IQ9	5.210	1.337	-0.583	-0.209		
	IQ10	4.950	1.445	-0.354	-0.874		
	IQ11	4.990	1.401	-0.378	-0.768		
	IQ12	4.880	1.394	-0.169	-0.877		
	IQ13	5.010	1.390	-0.476	-0.489		
	IQ14	4.960	1.416	-0.274	-0.818		
	IQ15	4.940	1.536	-0.269	-0.924		
Information Source (IS)	IS1	5.150	1.309	-0.588	-0.323	5.077	1.186
	IS2	5.190	1.355	-0.705	0.009		
	IS3	4.990	1.411	-0.382	-0.695		
	IS4	5.120	1.385	-0.498	-0.491		
	IS5	4.940	1.402	-0.404	-0.642		
Information Channel (IC)	IC1	5.050	1.450	-0.764	0.131	5.199	1.174
	IC2	5.210	1.372	-0.541	-0.484		
	IC3	5.250	1.333	-0.738	-0.092		

Construct	Item	Mean	Std. Deviation	Skewness	Kurtosis	Construct's Mean	Construct's Std. Deviation
	IC4	5.280	1.349	-0.678	-0.262		
	IC5	5.130	1.320	-0.596	-0.319		
	IC6	5.180	1.372	-0.472	-0.371		
	IC7	5.250	1.347	-0.658	-0.258		
	IC8	5.250	1.426	-0.559	-0.452		
Perceived Usefulness (PU)	PU1	4.840	1.527	-0.291	-0.866	4.843	1.444
	PU2	4.820	1.616	-0.453	-0.793		
	PU3	4.880	1.613	-0.483	-0.682		
	PU4	4.830	1.489	-0.431	-0.594		
Health Information Adoption (HIA)	HIA1	5.010	1.534	-0.615	-0.599	5.025	1.393
	HIA2	4.980	1.584	-0.553	-0.683		
	HIA3	5.030	1.472	-0.443	-0.575		
	HIA4	5.090	1.526	-0.557	-0.364		
Level of Knowledge (LK)	LK1	5.200	1.389	-0.672	-0.111	5.167	1.212
	LK2	5.140	1.277	-0.652	0.083		
	LK3	5.160	1.347	-0.412	-0.595		
Cognitive Involvement (CI)	CI1	5.250	1.344	-0.685	-0.016	5.249	1.197
	CI2	5.300	1.331	-0.703	-0.025		
	CI3	5.200	1.334	-0.590	-0.355		

Table 7.2: Descriptive Statistics

7.3 Reliability and Validity Analysis

Building upon the pre-survey results (n=120) discussed in Chapter 6, this study also conducted reliability and validity analyses on the final survey data (n=500).

7.3.1 Reliability Analysis

Similar to the pre-survey analysis, Cronbach's alpha coefficient was employed to examine the internal consistency within each dimension. As shown in Table 7.3, Cronbach's alpha coefficients for all latent variables exceeded 0.877, with an overall value of 0.969, indicating excellent internal consistency of the measurement scales (Nunnally and Bernstein, 1994). In the subsequent Confirmatory Factor Analysis, standardised factor loadings were extracted, with CR and AVE indicators further reported in 7.3.2.2 to evaluate the reliability and validity levels of the scales comprehensively.

Construct	Cronbach's α	N of Items
Information Quality (IQ)	0.967	15
Information Source (IS)	0.915	5
Information Channel (IC)	0.948	8
Perceived Usefulness (PU)	0.943	4
Health Information Adoption (HIA)	0.932	4
Level of Knowledge (LK)	0.890	3
Cognitive Involvement (CI)	0.877	3
Total Variables	0.969	42

Table 7.3: The Results of Reliability Analysis

7.3.2 Confirmatory Factor Analysis and Validity Analysis

Unlike Exploratory Factor Analysis (EFA) used in pre-survey, CFA is based on prior theoretical assumptions and aims to validate predetermined factor structures (Hair et al., 2018). This study employs CFA to evaluate the fit of the measurement model and the validity of each indicator variable, mainly including both overall model fit evaluation and construct validity testing.

7.3.2.1 CFA Model Fit Evaluation

As illustrated in Figure 7.1, the CFA model included seven latent variables and 42 observed variables. Model fit was assessed using multiple indicators, including χ^2/df, RMSEA, NFI, IFI, TLI, and CFI (Kline, 2015).

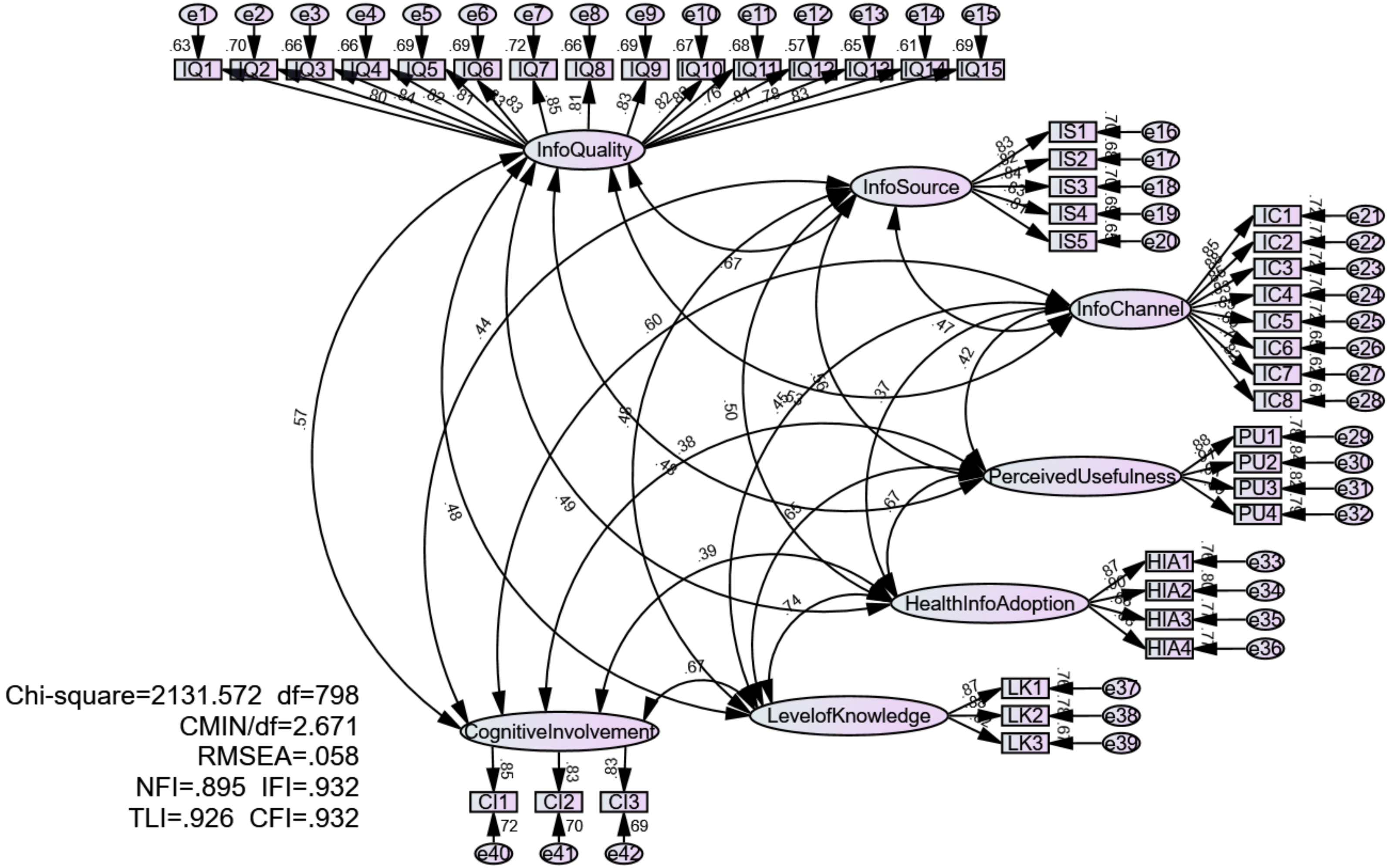

Figure 7.1: CFA Model

Table 7.4 presents the model fit indices. The chi-square/degrees of freedom ratio (χ^2/df) is 2.671, less than the critical value of 3, indicating a good model fit. The Root Mean Square Error of Approximation (RMSEA), which accounts for model complexity and sample size, shows a value of 0.058. This falls below the recommended threshold of 0.08, indicating a good model fit and suggesting a reasonable error of approximation in the population. The Incremental Fit Index (IFI) is 0.932, the Tucker-Lewis Index (TLI) is 0.926, and the Comparative Fit Index (CFI) is 0.932, all exceeding the recommended threshold of 0.90. Whilst the Normed Fit Index (NFI) is 0.895, was marginally below 0.9, considering its sensitivity to sample size (Anderson and Gerbing, 1984) and the strong performance of other indicators, the measurement model demonstrated a good fit with the empirical data.

Model Fit Indices	Thresholds	Values
CMIN/*df*	1-3	2.671
RMSEA	<0.08	0.058
NFI	>0.9	0.895
IFI	>0.9	0.932
TLI	>0.9	0.926
CFI	>0.9	0.932

Table 7.4: CFA Model Fit Results

7.3.2.2 Convergent Validity

The assessment of convergent validity examined standardised factor loadings, Average Variance Extracted (AVE), and Composite Reliability (CR). According to established criteria (Hair et al., 2018), standardised factor loadings should be ≥ 0.7, AVE should be ≥ 0.5, and CR should be ≥ 0.7. As presented in Table 7.5, all standardised factor loadings exceeded 0.7 (with the lowest being 0.758), AVE values ranged from 0.665 to 0.807, and CR values spanned from 0.877 to 0.968, all meeting the standard requirements. These results indicated that the latent variables demonstrated good internal consistency and effectively explained the corresponding observed variables, exhibiting strong measurement convergence.

Construct		Standardised Loading	AVE	CR
Information Quality	IQ1	0.796	0.665	0.968
	IQ2	0.837		
	IQ3	0.815		
	IQ4	0.810		
	IQ5	0.830		
	IQ6	0.829		
	IQ7	0.848		
	IQ8	0.813		
	IQ9	0.830		
	IQ10	0.821		
	IQ11	0.824		
	IQ12	0.758		
	IQ13	0.807		
	IQ14	0.780		
	IQ15	0.832		
Information Source	IS1	0.834	0.684	0.915
	IS2	0.825		
	IS3	0.838		
	IS4	0.832		
	IS5	0.806		
Information Channel	IC1	0.848	0.695	0.948
	IC2	0.876		
	IC3	0.847		
	IC4	0.835		
	IC5	0.847		
	IC6	0.804		
	IC7	0.789		
	IC8	0.820		
Perceived Usefulness	PU1	0.883	0.807	0.944
	PU2	0.915		
	PU3	0.907		
	PU4	0.888		
Health Information Adoption	HIA1	0.870	0.774	0.932
	HIA2	0.896		
	HIA3	0.876		
	HIA4	0.876		
Level of Knowledge	LK1	0.870	0.735	0.893
	LK2	0.882		
	LK3	0.819		
Cognitive Involvement	CI1	0.850	0.705	0.877
	CI2	0.835		
	CI3	0.833		

Table 7.5: The Results of Convergent Validity Analysis

7.3.2.3 Discriminant Validity

Discriminant validity was assessed by comparing the square root of AVE with the correlation coefficients between latent variables (Fornell and Larcker, 1981). Additionally, correlation coefficients between constructs should not exceed 0.85 to avoid potential collinearity issues (Kline, 2015). Table 7.6 presents the square roots of AVE and correlation coefficients for each latent variable.

	IQ	IS	IC	PU	HIA	LK	CI
IQ	**0.815**						
IS	0.671	**0.827**					
IC	0.533	0.469	**0.834**				
PU	0.476	0.555	0.422	**0.898**			
HIA	0.490	0.501	0.370	0.671	**0.880**		
LK	0.480	0.478	0.446	0.652	0.739	**0.857**	
CI	0.568	0.444	0.603	0.381	0.392	0.669	**0.840**
AVE	0.665	0.684	0.695	0.807	0.774	0.735	0.705
Sqrt of (AVE)	0.815	0.827	0.834	0.898	0.880	0.857	0.840
Note: The elements on the diagonal represent the square root of the average variance extracted (AVE) and the values outside the diagonal represent the correlations between the constructs. IQ: Information Quality; IS: Information Source; IC: Information Channel; PU: Perceived Usefulness; HIA: Health Information Adoption; LK: Level of Knowledge; CI: Cognitive Involvement.							

Table 7.6: Discriminant Validity

The results showed that the square root of AVE values on the diagonal were all greater than the corresponding row and column correlation coefficients, and all correlation coefficients remained well below 0.85. These findings indicated good discriminant validity among the latent variables, effectively distinguishing different conceptual constructs and avoiding collinearity issues caused by construct overlap.

The measurement model thus demonstrated excellent performance in both convergent and discriminant validity, providing a reliable foundation for subsequent structural model analysis, path analysis, and hypothesis testing, thereby ensuring the validity and credibility of the research results.

7.4 Structural Equation Modelling

Structural Equation Modelling (SEM) represents a comprehensive multivariate statistical analysis method that enables the simultaneous examination of relationships among multiple latent and observed variables (Hair et al., 2018). This study employs SEM to validate the theoretical model of health information adoption on social media through four sequential stages: Model Specification, Model Identification, Model Estimation, and Model Fit Evaluation. Each stage builds upon the previous one to ensure analytical rigour and result reliability.

7.4.1 Model Specification

Model specification forms the foundational stage of SEM analysis, wherein the relationships between variables are theoretically defined and empirically justified. Drawing from the qualitative findings presented in Chapter 5 and the theoretical framework developed in Chapter 6, the study establishes a structural model incorporating three exogenous latent variables: Information Quality (IQ) with fifteen measurement indicators (IQ1-IQ15), Information Source (IS) with five measurement indicators (IS1-IS5), and Information Channel (IC) with eight measurement indicators (IC1-IC8). The model further includes Perceived Usefulness (PU) as a mediating latent variable measured through four indicators (PU1-PU4) and Health Information Adoption (HIA) as the dependent variable with four measurement indicators (HIA1-HIA4). The hypothesised relationships among these variables are clearly specified, forming the basis for the structural and measurement components of the model, as shown in Figure 7.2.

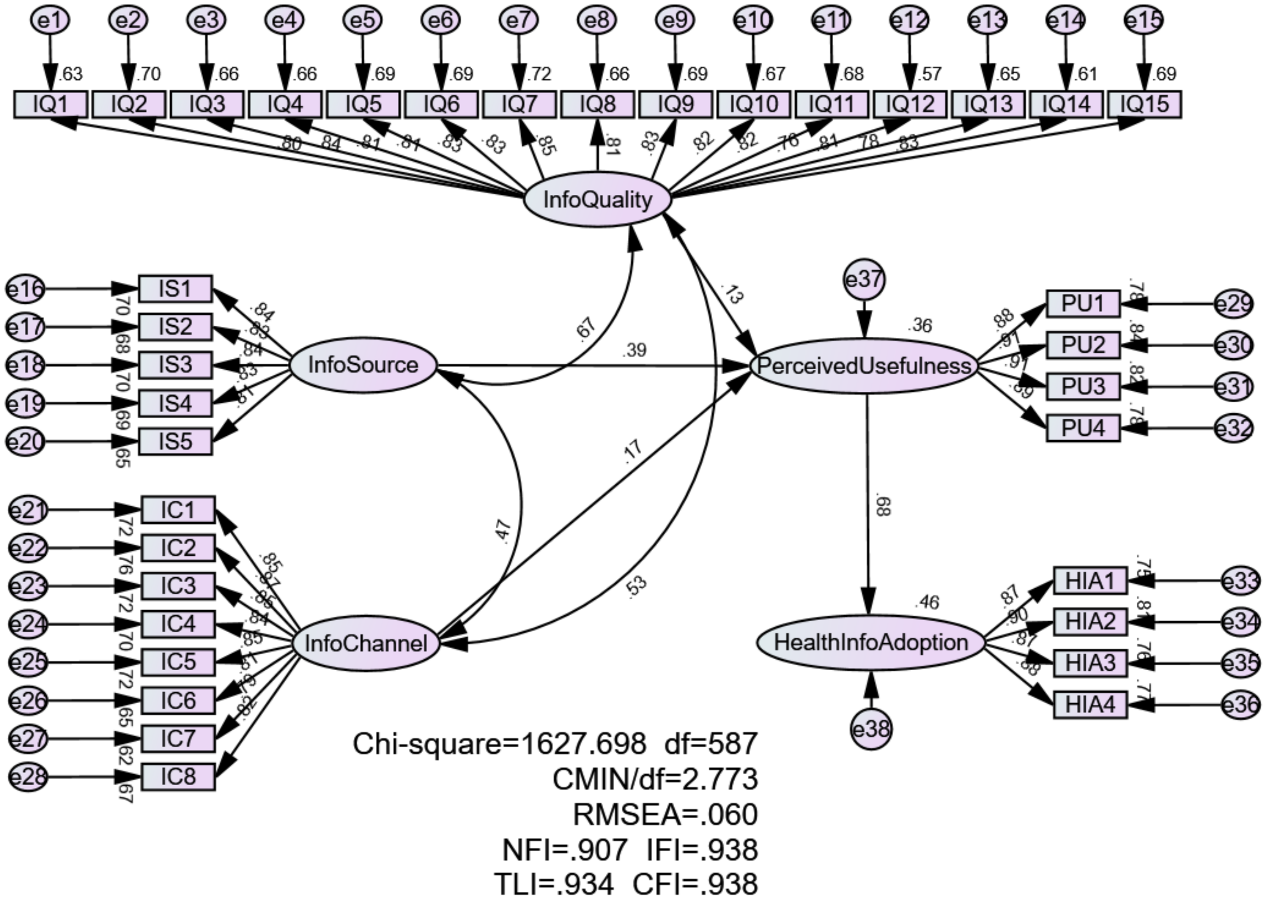

Figure 7.2: SEM Model

The theoretical model proposes several key hypothesised relationships that form the foundation of the structural and measurement components. In the structural model part, Information Quality (IQ), Information Source (IS), and Information Channel (IC) are hypothesised to have positive influence paths on Perceived Usefulness (PU). At the same time, PU is proposed to positively influence Health Information Adoption (HIA), thereby functioning as a mediating variable. The measurement model part includes the relationships between each latent variable and its corresponding measurement indicators, establishing the measurement framework for the analysis.

A significant methodological consideration in this study involves the treatment of moderating variables—Level of Knowledge (LK) and Cognitive Involvement (CI). These variables, while theoretically important, are not incorporated into the primary SEM model due to several technical constraints inherent to structural equation modelling. SEM's fundamental assumptions and analytical framework are not well-suited for examining moderating effects, as these effects do not establish direct paths and cannot be properly treated as endogenous or exogenous variables within the SEM framework. Furthermore, while SEM focuses on analysing path coefficients under the assumption of linear relationships, moderating effect analysis requires the examination of interaction term coefficients, which inherently involve product terms that violate the linearity assumption of SEM.

To address these methodological challenges while ensuring a comprehensive analysis of all hypothesised relationships, this study adopts a dual-analytical approach. The core influence paths, and mediating effects are examined through SEM, while the moderating effects are analysed separately using the SPSS Process Macro in 7.5.2. This strategic combination of analytical methods utilises the unique advantages of both approaches: SEM's capability to handle complex path relationships and Process Macro's specialisation in moderating effect analysis. This integrated analytical strategy enables a more subtle and accurate examination of the complete theoretical framework, ultimately providing a more thorough understanding of the mechanisms underlying health information adoption on social media.

7.4.2 Model Identification

Model identification is necessary for assessing whether the SEM model has unique estimated values. In this study, ensuring proper model identification is primarily achieved through the following aspects:

Measurement model identification

Each latent variable is constructed and defined by at least three measurement indicators. For example, IQ has fifteen indicators, IS has five indicators, IC has eight indicators, and PU and HIA each have four indicators. This not only satisfies the over-identified condition but also improves measurement reliability. The scale for each latent variable is set. In this study, this is achieved by fixing the factor loading of one measurement indicator for each latent variable to 1.

Structural model identification

The constructed path relationships are recursive, with no feedback loops. For instance, IQ, IS, and IC influence PU, and PU influence HIA; these relationships are unidirectional, satisfying the recursive condition. Covariance relationships are allowed between exogenous latent variables (IQ, IS, IC), reflecting possible inter-correlations between information characteristics.

Overall model identification

The total degrees of freedom of the model are calculated to ensure they are greater than zero. In this study, the number of observed variables is 42, and the number of parameters to be estimated is far less than 42(42+1)/2=903, satisfying the over-identified condition.

7.4.3 Model Estimation

The study implements Maximum Likelihood Estimation (MLE) through AMOS 26.0 to determine optimal parameter values that best reproduce the sample covariance matrix. MLE represents the most widely adopted estimation method in SEM research, offering robust results, particularly when working with large samples and normally distributed data (Byrne, 2016). The estimation process includes two parts: the measurement model and the structural model. In the measurement model part, the factor loadings of each latent variable (IQ, IS, IC, PU, HIA) and the error variances of various measurement indicators are mainly estimated. In the structural model part, the standardised and non-standardised path coefficients of relationships between latent variables, as well as the residual variances of endogenous latent variables (PU and HIA), are estimated.

During the estimation process, AMOS gradually approximates the best-fit parameter values between the model and actual data through iterative calculations, stopping iteration when parameter estimates reach convergence. The model in this study achieved convergence after 12 iterations, indicating good stability and convergence speed of the model. The constructed SEM model includes the theoretical relationship paths between information characteristics (IQ/IS/IC), perceived usefulness (PU), and health information adoption (HIA).

7.4.4 SEM Model Fit Evaluation

Model fit evaluation examines the alignment between the theoretical model and empirical data through multiple fit indices. As shown in Table 7.7, the analysis reveals a Chi-square/degrees of freedom ratio (CMIN/*df*) of 2.773, falling within the acceptable range of 1-3, while the Root Mean Square Error of Approximation (RMSEA) value of

0.060 remains below the 0.08 threshold, indicating good approximate fit. The incremental fit indices further support the model's validity, with the Normed Fit Index (NFI) at 0.907, Incremental Fit Index (IFI) at 0.938, Tucker-Lewis Index (TLI) at 0.934, and Comparative Fit Index (CFI) at 0.938, all exceeding the conventional threshold of 0.90 (Hu and Bentler, 1999).

Model Fit Indices	**Thresholds**	**Values**
CMIN/*df*	1-3	2.773
RMSEA	<0.08	0.060
NFI	>0.9	0.907
IFI	>0.9	0.938
TLI	>0.9	0.934
CFI	>0.9	0.938

Table 7.7: SEM Model Fit Results

Synthesising the above indices, it can be concluded that the theoretical model of social media health information adoption constructed in this study achieves a good fit with the actual data, with all indices passing the test criteria.

7.5 Path Analysis

The complexity of health information adoption behaviour on social media necessitates a sophisticated analytical approach that can capture both direct and indirect relationships between variables. This study employs a comprehensive analytical strategy combining Structural Equation Modelling (SEM) through AMOS 26.0 for mediation analysis and SPSS 29.0 Process Macro v4.2 for moderation analysis. This methodological choice merits critical consideration, as whilst each approach offers distinct advantages, they also present certain limitations (Hayes, 2018a). The integrated use of these complementary techniques enables a more subtle understanding of the complex mechanisms underlying health information adoption behaviour.

7.5.1 Mediation Effect Analysis

This study employs AMOS 26.0 to construct a comprehensive mediation path model, as illustrated in Figure 7.3. The model incorporates three independent variables (Information Quality IQ, Information Source IS, Information Channel IC), one mediating variable (Perceived Usefulness PU), and one dependent variable (Health Information Adoption HIA). This structural equation modelling (SEM) approach was selected based on several methodological advantages that make it particularly suitable for analysing complex relationships in social media health information adoption behaviour.

The primary advantage of using SEM lies in its ability to simultaneously estimate complex path relationships between multiple variables. This capability helps avoid potential collinearity and error accumulation problems that might arise when analysing multiple relationships separately. Furthermore, the AMOS platform supports the Bootstrap method for significance testing of mediation effects, which proves particularly valuable as it operates under more relaxed assumptions about sample distribution and provides more robust and reliable results (Hayes, 2018a). The SEM approach also excels in handling both latent and observed variables, making it especially suitable for examining constructs with multiple measurement indicators, thereby enabling a more comprehensive capture of variable relationships (Kline, 2015). Additionally, AMOS provides various model fit indices that allow for a thorough evaluation of the compatibility between the theoretical model and empirical data (Brown, 2015).

The mediation analysis in this study follows a systematic three-step approach to thoroughly examine the relationships between variables and test the proposed mediation effects. First, construct the mediation path model and evaluate the overall model fit (7.5.1.1); second, examine the significance of path coefficients from independent variables to the mediating variable and from the mediating variable to the dependent variable to confirm that conditions for testing mediation effects are met (7.5.1.2); finally, estimate the size proportions of various effects through user-defined statements, use the Bootstrap method to test the significance of indirect effects, and calculate the proportion of indirect effects in total effects to quantify and explain the role of mediation effects in the entire model (7.5.1.3).

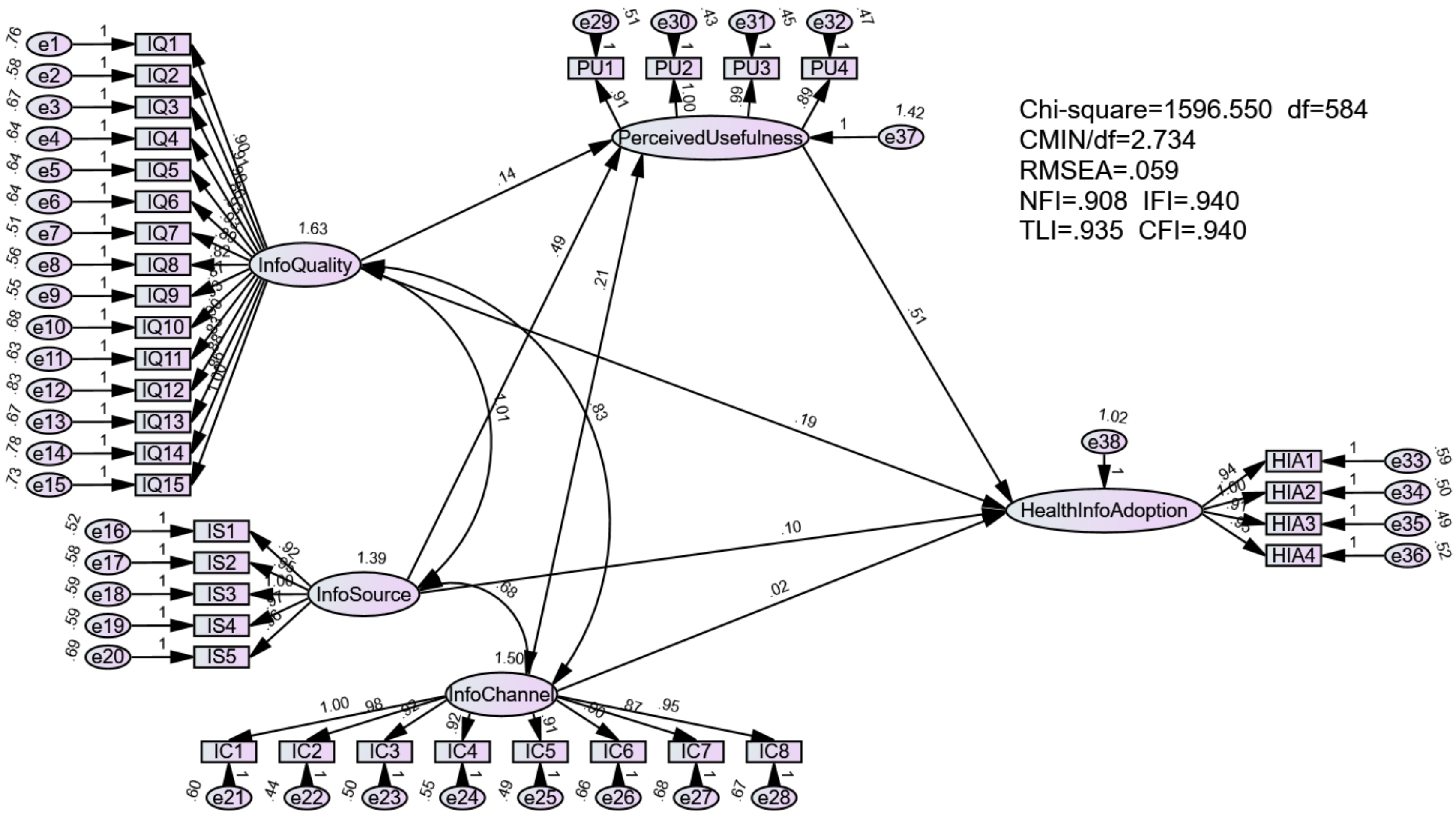

Figure 7.3: Mediation Path Model

7.5.1.1 Model Fit Evaluation

To comprehensively assess the goodness of fit of the mediation path model, this study adopts multiple indices for synthetic judgment. Table 7.8 presents detailed results of model fit indices. The chi-square/degrees of freedom ratio (χ^2/df) is 2.734, less than the critical value of 3, indicating a good model fit. The Root Mean Square Error of Approximation (RMSEA), which accounts for model complexity and sample size, shows a value of 0.059. This falls below the recommended threshold of 0.08, indicating a good model fit and suggesting a reasonable error of approximation in the population. The Normed Fit Index (NFI) is 0.908, the Incremental Fit Index (IFI) is 0.940, the Tucker-Lewis Index (TLI) is 0.935, and the Comparative Fit Index (CFI) is 0.940, all exceeding the recommended threshold of 0.90. These results collectively indicate that the mediation path model demonstrates a strong fit with the empirical data, providing a solid foundation for subsequent path analysis and hypothesis testing.

Model Fit Indices	Thresholds	Values
CMIN/*df*	1-3	2.734
RMSEA	<0.08	0.059
NFI	>0.9	0.908
IFI	>0.9	0.940
TLI	>0.9	0.935
CFI	>0.9	0.940

Table 7.8: Mediation Path Model Fit Results

7.5.1.2 Path Coefficient Testing

The analysis of path coefficients reveals several significant relationships between the model's variables. Table 7.9 presents the detailed results of standardised and non-standardised path coefficients of the mediation path model. The examination of these relationships begins with the effects of the three independent variables on Perceived Usefulness (PU). Information Quality (IQ) demonstrates a significant positive effect on PU ($\beta = 0.120$, $p < 0.05$), suggesting that high-quality health information enhances users' perception of its usefulness. Information Source (IS) exhibits the strongest influence on PU ($\beta = 0.393$, $p < 0.001$), highlighting the crucial role of reliable information sources in shaping users' perceptions of information usefulness. Similarly, Information Channel (IC) exhibits a significant positive effect on PU ($\beta = 0.173$, $p < 0.001$), indicating that effective information dissemination channels contribute meaningfully to users' perception of information usefulness. The relationship between Perceived Usefulness and Health Information Adoption (HIA) emerges as particularly robust ($\beta = 0.535$, $p < 0.001$), underscoring the central role of perceived usefulness in facilitating health information adoption behaviour.

Path			Unstd. Estimate	Std. Estimate	S.E.	C.R.	P
PU	<---	IQ	0.139	0.120	0.067	2.055	0.040
PU	<---	IS	0.491	0.393	0.073	6.691	***
PU	<---	IC	0.208	0.173	0.058	3.590	***
HIA	<---	PU	0.512	0.535	0.047	10.946	***
HIA	<---	IQ	0.194	0.175	0.059	3.277	0.001
HIA	<---	IS	0.097	0.081	0.067	1.449	0.147
HIA	<---	IC	0.017	0.015	0.051	0.338	0.735

Table 7.9: The Results of the Mediation Path Coefficient

When examining the direct effects of independent variables on HIA, Information Quality maintains a significant positive influence ($\beta = 0.175$, $p < 0.01$), suggesting that high-quality health information can directly promote adoption behaviour. However, neither the Information Source ($\beta = 0.081$, $p > 0.05$) nor the Information Channel ($\beta = 0.015$, $p > 0.05$) demonstrates significant direct effects on HIA, indicating that these factors might primarily influence information adoption through indirect pathways.

7.5.1.3 Mediation Effect Testing and Analysis

The examination of mediation effects employed user-defined estimation statements to calculate indirect effects, direct effects, and total effects for each independent variable.

Figure 7.4 illustrates the path coefficients used in the analysis, where paths a1, a2, and a3 represent coefficients from independent variables to PU, path b represents the coefficient from PU to HIA, and paths c1, c2, and c3 represent direct paths from independent variables to HIA.

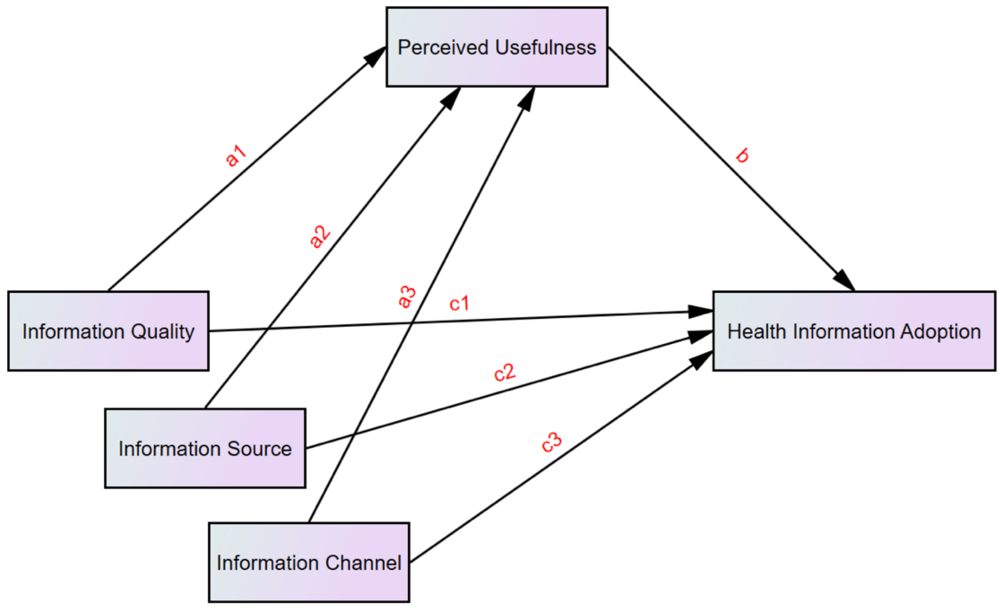

Figure 7.4: Estimating User-defined Estimands Path Coefficient

Then, input the following user-defined estimation statements for mediation effect analysis in this study:

ind1 = p.a1 * p.b (Indirect effect of IQ on HIA through PU)

ind2 = p.a2 * p.b (Indirect effect of IS on HIA through PU)

ind3 = p.a3 * p.b (Indirect effect of IC on HIA through PU)

dir1 = p.c1 (Direct effect of IQ on HIA)

dir2 = p.c2 (Direct effect of IS on HIA)

dir3 = p.c3 (Direct effect of IC on HIA)

total1 = ind1 + dir1 (Total effect of IQ on HIA)

total2 = ind2 + dir2 (Total effect of IS on HIA)

total3 = ind3 + dir3 (Total effect of IC on HIA)

This study adopted the Bootstrap method for analysis to examine mediation effects deeply. The sample size was set to 5000, and the confidence interval was 95%. Table 7.10 presents detailed results of mediation effect analysis, revealing three different patterns of mediation effects.

Parameter		**Estimate**	**Lower**	**Upper**	**P**	**Effect %**
Indirect Effect	IQ	0.071	-0.012	0.158	0.094	0.268
	IS	0.252	0.144	0.399	0.001	0.722
	IC	0.107	0.040	0.183	0.003	0.863
Direct Effect	IQ	0.194	0.012	0.372	0.039	0.732
	IS	0.097	-0.118	0.293	0.368	0.278
	IC	0.017	-0.132	0.166	0.842	0.137
Total Effect	IQ	0.265	0.098	0.422	0.002	
	IS	0.349	0.187	0.525	0.001	
	IC	0.124	-0.018	0.262	0.084	

Table 7.10: The Results of the Mediation Effect

The analysis of Information Quality's effect on Health Information Adoption demonstrates that Perceived Usefulness serves as a partial mediator in this relationship. The indirect effect through Perceived Usefulness (0.071, 95% CI: -0.012~0.158) shows marginal significance, while the direct effect (0.194, $p < 0.05$) constitutes a substantial 73.2% of the total effect (0.265, $p < 0.01$). This finding reveals an interesting dynamic where the direct influence of information quality dominates the adoption process, suggesting that users may rely more heavily on their direct assessment of information quality rather than their perceptions of its usefulness. This pattern challenges the assumption that perceived usefulness is always the primary driver of information adoption and highlights the sophisticated nature of users' evaluation processes.

For Information Sources, the analysis reveals that Perceived Usefulness acts as a full mediator, marking a distinctly different pattern from Information Quality. The indirect effect (0.252, 95% CI: 0.144~0.399, $p < 0.01$) accounts for a substantial 72.2% of the total effect (0.349, $p < 0.01$), while the direct effect (0.097, $p > 0.05$) lacks statistical significance. This finding critically suggests that the influence of information sources on adoption behaviour operates entirely through users' perceptions of usefulness rather than through direct trust or authority. This mechanism highlights the importance of establishing and maintaining source credibility as a means of enhancing perceived usefulness rather than relying solely on source authority.

The relationship between Information Channel and Health Information Adoption follows a similar full mediation pattern through Perceived Usefulness, yet with its own distinct characteristics. The indirect effect (0.107, 95% CI: 0.040~0.183, $p < 0.01$) represents an overwhelming 86.3% of the total effect (0.124, $p = 0.084$), with no significant direct effect (0.017, $p > 0.05$). This finding is particularly noteworthy as it suggests that the effectiveness of information channels is almost entirely dependent on how they enhance users' perceptions of information usefulness. This challenges traditional assumptions about the direct impact of channel characteristics on information adoption and emphasises the need for channel optimisation strategies that specifically target user perceptions of usefulness.

Path	Coefficient	Result	Implication
IQ→PU	0.120* (p=0.040)	Significant Positive	Higher information quality enhances perceived usefulness.
IS→PU	0.393*** (p<0.001)	Significant Positive	Reliable information sources significantly boost perceived usefulness.
IC→PU	0.173*** (p<0.001)	Significant Positive	Effective information channel improves perceived usefulness.
PU→HIA	0.535*** (p<0.001)	Significant Positive	Perceived usefulness greatly increases health information adoption.
IQ→HIA	0.175*** (p=0.001)	Significant Positive	High information quality directly influences health information adoption.
IS→HIA	0.081 (p=0.147)	Not Significant	Information source alone does not directly affect health information adoption.
IC→HIA	0.015 (p=0.735)	Not Significant	Information channel alone does not directly affect health information adoption.
IQ→PU→HIA	0.071 (p=0.094)	Marginally Significant (95% CI: -0.120~0.158) Partial Mediation	Perceived usefulness partially mediates the impact of information quality on health information adoption.
IS→PU→HIA	0.252*** (p=0.001)	Significant Positive (95% CI: 0.144~0.399) Full Mediation	Perceived usefulness fully mediates the relationship between information source and health information adoption.
IC→PU→HIA	0.107** (p=0.003)	Significant Positive (95% CI: 0.040~0.183) Full Mediation	Perceived usefulness fully mediates the relationship between information channel and health information adoption.
Note: ***p<.001, **p<.01, *p<.05; IQ: Information Quality; IS: Information Source; IC: Information Channel; PU: Perceived Usefulness; HIA: Health Information Adoption.			

Table 7.11: Summary of Direct and Indirect Effects

Table 7.11 synthesises these key findings, presenting a comprehensive summary of both direct and mediation effects in the research model. The results support hypotheses H1-H4, showing significant positive relationships between Information Quality (H1), Information Source (H2), Information Channel (H3) and Perceived Usefulness, as well as between Perceived Usefulness (H4) and Health Information Adoption. The mediation analysis further supports H5-H7, revealing distinct patterns of influence: Information Quality (H5) demonstrates partial mediation through Perceived Usefulness, whilst both Information Source (H6) and Information Channel (H7) show full mediation effects. These findings suggest that whilst information quality can directly influence adoption decisions, the effects of sources and channels operate primarily by shaping users' perceptions of information utility, providing important insights for health information dissemination strategies on social media.

7.5.2 Moderation Effect Analysis

The moderation effect analysis examines how individual differences influence the relationships in the theoretical model. This analysis was conducted using the SPSS 29.0 Process Macro v4.2, which is particularly effective for testing moderation effects through its specialised procedures (Hayes, 2018b). The Process Macro was chosen because it provides reliable statistical analysis and clear result interpretation, which are essential for understanding the complex relationships in social media health information adoption.

The selection of the Process Macro was based on four main advantages. Firstly, it provides Model 1 as a pre-set template that ensures reliable results and straightforward operation, as shown in Figure 7.5. Secondly, it supports the percentile bootstrap confidence interval method, which strengthens the testing of moderation effects. Thirdly, it generates clear statistical indicators that help interpret the moderation effects directly. Fourthly, it offers functionality for creating visual representations of the moderation effects through conditional effect plots (Preacher and Hayes, 2008).

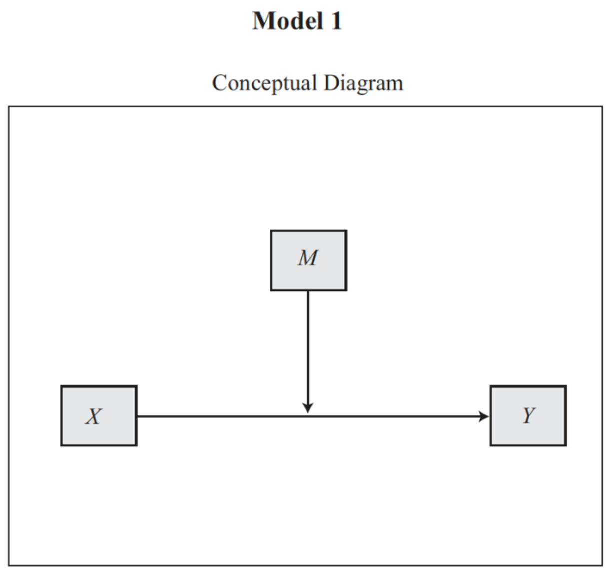

Figure 7.5: SPSS Process Model 1 Conceptual Diagram

The analysis process consisted of four main steps to thoroughly examine each hypothesised moderation effect. In the first step, the variables were input into Process Macro Model 1. For examining the moderating effects of level of knowledge (LK), three separate analyses were conducted: one each for information quality (IQ), information source (IS), and information channel (IC) as independent variables, with perceived usefulness (PU) as the dependent variable. A fourth analysis examined how cognitive involvement (CI) moderates the relationship between perceived usefulness (PU) and health information adoption (HIA). The second step involved testing whether each moderation effect was statistically significant, focusing particularly on the interaction terms and their significance values. The third step analysed the nature of significant moderation effects, examining how the relationships changed under different moderator values. The final step included creating visual representations to clearly show how the moderating variables influenced these relationships.

7.5.2.1 LK on ‘IQ→PU’

The first moderation analysis examined how the level of knowledge (LK) influences the relationship between information quality (IQ) and perceived usefulness (PU). The analysis using Process Model 1 revealed significant results, as presented in Table 7.12. The overall model demonstrated strong explanatory power with $R^2 = .411$, indicating that the model could explain approximately 41.1% of the variance in perceived usefulness. The model's statistical significance ($F(3, 496) = 115.42$, $p < .001$) confirms its robust predictive capability.

Variable	**Coeff.**	**SE**	**t**	**p**	**LLCI**	**ULCI**
Constant	4.7764	0.0552	86.4529	0.0000	4.6679	4.8850
IQ	0.2652	0.0489	5.4210	0.0000	0.1691	0.3614
LK	0.6081	0.0467	13.0102	0.0000	0.5162	0.6999
IQ × LK	0.1040	0.0377	2.7591	0.0060	0.0299	0.1781
$R^2 = 0.4111$, $F(3, 496) = 115.4220$, $p < 0.001$						

Table 7.12: Moderation Effect of LK on ‘IQ→PU’

The analysis revealed significant main effects for both information quality ($\beta = .265$, $p < .001$) and level of knowledge ($\beta = .608$, $p < .001$) on perceived usefulness. These results indicate that both variables independently contribute to users' perceptions of information usefulness. Notably, the interaction term between information quality and level of knowledge (IQ × LK) showed a significant positive effect ($\beta = .104$, $p = .006$), supporting hypothesis H8a. This interaction suggests that the impact of information quality on perceived usefulness varies meaningfully across different levels of knowledge.

To better understand the nature of this moderating effect, the analysis examined the conditional effects of information quality on perceived usefulness at different levels of knowledge, as shown in Table 7.13. The results revealed a pattern where the relationship between information quality and perceived usefulness strengthens as users' knowledge levels increase. At low knowledge levels (-1 SD), the relationship was marginally significant (β = .139, p = .057). However, at mean knowledge levels, the relationship became notably stronger (β = .265, p < .001), and at high knowledge levels (+1 SD), the relationship was strongest (β = .391, p < .001).

LK	Effect	SE	t	p	LLCI	ULCI
-1.2122	0.1392	0.0729	1.9097	0.0567	-0.0040	0.2823
0.0000	0.2652	0.0489	5.4210	0.0000	0.1691	0.3614
1.2122	0.3913	0.0605	6.4725	0.0000	0.2725	0.5101

Table 7.13: Conditional Effects of IQ on PU at Values of LK

This pattern is visually represented in Figure 7.6, illustrating how the positive relationship between information quality and perceived usefulness becomes more pronounced as knowledge levels increase. The steeper slope for high knowledge levels indicates that users with greater domain knowledge are more sensitive to variations in information quality when evaluating information usefulness.

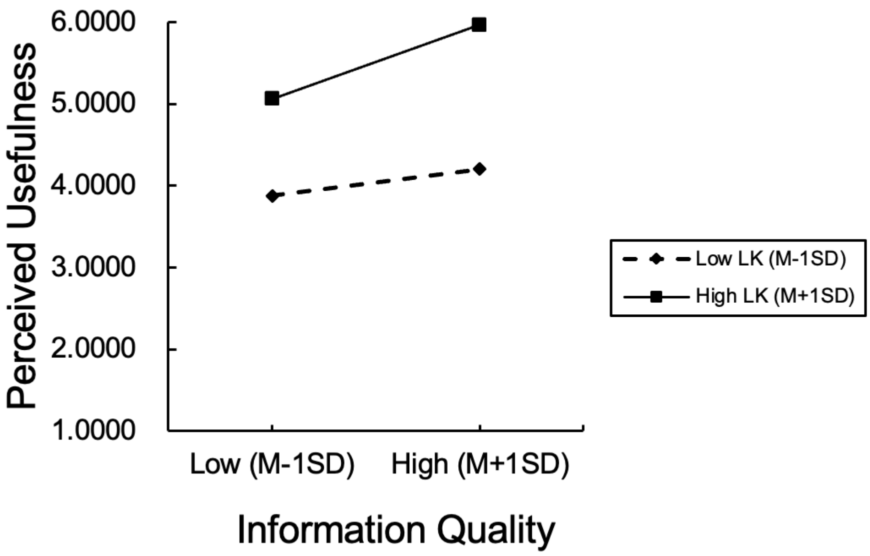

Figure 7.6: Moderation Effect of LK on the Relationship between 'IQ and PU'

This pattern of results suggests that domain knowledge plays a critical role in how users evaluate health information quality on social media platforms. The strengthening relationship between information quality and perceived usefulness at higher knowledge levels indicates that users with greater domain expertise are more capable of discerning and appreciating quality differences in health information. This finding provides valuable insights for targeting health information dissemination strategies to different audience segments based on their knowledge levels.

7.5.2.2 LK on 'IS→PU'

The second moderation analysis investigated how the level of knowledge (LK) influences the relationship between information source (IS) and perceived usefulness (PU). Table 7.14 presents the results of this analysis using Process Model 1. The model demonstrated substantial explanatory power with $R^2 = .442$, explaining approximately 44.2% of the variance in perceived usefulness. The overall model showed strong statistical significance ($F(3, 496) = 130.81$, $p < .001$), indicating its robust predictive capability.

Variable	**Coeff.**	**SE**	**t**	**p**	**LLCI**	**ULCI**
Constant	4.8737	0.0541	90.1545	0.0000	4.7675	4.9800
IS	0.3955	0.0461	8.5779	0.0000	0.3049	0.4861
LK	0.5428	0.0447	12.1482	0.0000	0.4550	0.6306
IS × LK	-0.0492	0.0385	-1.2757	0.2026	-0.1249	0.0266
$R^2 = 0.4417$, $F(3, 496) = 130.8148$, $p < 0.001$						

Table 7.14: Moderation Effect of LK on 'IS→PU'

The analysis revealed significant main effects for both information source ($\beta = .396$, $p < .001$) and level of knowledge ($\beta = .543$, $p < .001$) on perceived usefulness, suggesting that both variables independently contribute to users' perceptions of information usefulness. However, contrary to expectations, the interaction term between information source and level of knowledge (IS × LK) was not significant ($\beta = -.049$, p

= .203). This finding does not support hypothesis H8b, indicating that the relationship between information source and perceived usefulness remains relatively stable across different knowledge levels.

The non-significant moderation effect is particularly noteworthy when considered within the broader context of health information processing on social media. Whilst users' level of knowledge significantly affects their perception of information usefulness, it does not appear to influence how they evaluate information sources. This finding suggests that the impact of source credibility on perceived usefulness may operate through mechanisms different from those initially theorised. The consistent effect of information source across knowledge levels indicates that source credibility serves as a universal heuristic in evaluating health information, regardless of users' domain knowledge.

Figure 7.7 provides a visual representation of this relationship, showing nearly parallel lines illustrating the consistent effect of information source across different knowledge levels. This pattern reinforces the finding that the impact of information source on perceived usefulness remains relatively stable regardless of users' knowledge levels.

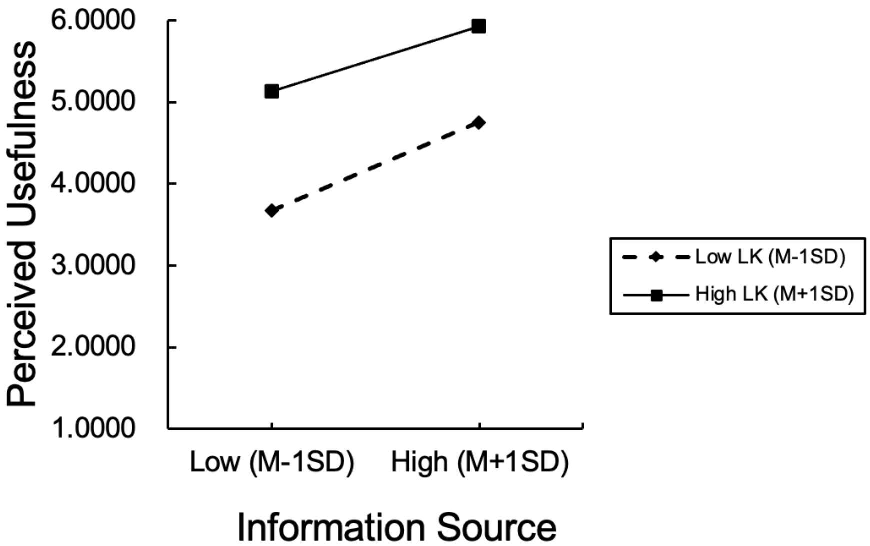

Figure 7.7: Moderation Effect of LK on the Relationship between 'IS and PU'

The non-significant moderation effect, combined with the strong main effects of both information source and knowledge level, suggests that source credibility serves as a universal heuristic in health information evaluation. The consistency of source effects across knowledge levels indicates that maintaining source credibility remains equally important for all user groups, regardless of their domain expertise.

7.5.2.3 LK on ‘IC→PU’

The third moderation analysis examined how the level of knowledge (LK) influences the relationship between information channel (IC) and perceived usefulness (PU). Table 7.15 presents the results of this analysis using Process Model 1. The model demonstrated strong explanatory power with $R^2 = .422$, explaining approximately 42.2% of the variance in perceived usefulness. The overall model showed robust statistical significance ($F(3, 496) = 120.56$, $p < .001$), indicating its reliable predictive capability.

Variable	Coeff.	SE	t	p	LLCI	ULCI
Constant	4.7366	0.0530	89.3714	0.0000	4.6324	4.8407
IC	0.2510	0.0463	5.4199	0.0000	0.1600	0.3419
LK	0.6284	0.0447	14.0744	0.0000	0.5407	0.7162
IC × LK	0.1819	0.0335	5.4367	0.0000	0.1161	0.2476
$R^2 = 0.4217$, $F(3, 496) = 120.5644$, $p < 0.001$						

Table 7.15: Moderation Effect of LK on ‘IC→PU’

The analysis identified significant main effects for both information channel ($\beta = .251$, $p < .001$) and level of knowledge ($\beta = .628$, $p < .001$) on perceived usefulness. Notably, the interaction term between information channel and level of knowledge (IC × LK) showed a substantial positive effect ($\beta = .182$, $p < .001$). This significant interaction supports hypothesis H8c, indicating that users’ knowledge levels meaningfully influence how information channel characteristics affect perceived usefulness.

To better understand this moderating effect, the analysis examined the conditional effects of information channel on perceived usefulness at different knowledge levels, as shown in Table 7.16. The results revealed a distinctive pattern where the relationship between information channel and perceived usefulness becomes progressively stronger with increasing knowledge levels. At low knowledge levels (-1 SD), the relationship was not significant ($\beta = .031$, $p = .603$), suggesting that users with limited domain knowledge may not effectively differentiate between channel characteristics. However, at mean knowledge levels, the relationship became significant and positive ($\beta = .251$, $p < .001$). The relationship was strongest at high knowledge levels (+1 SD) ($\beta = .471$, $p < .001$), indicating that users with greater domain knowledge are more sensitive to channel characteristics when evaluating information usefulness.

LK	Effect	SE	t	p	LLCI	ULCI
-1.2122	0.0305	0.0587	0.5202	0.6032	-0.0847	0.1457
0.0000	0.2510	0.0463	5.4199	0.0000	0.1600	0.3419
1.2122	0.4714	0.0643	7.3295	0.0000	0.3451	0.5978

Table 7.16: Conditional Effects of IC on PU at Values of LK

Figure 7.8 provides a visual representation of this moderating effect, clearly showing how the relationship between information channel and perceived usefulness becomes stronger as knowledge levels increase. The increasing slope at higher knowledge levels suggests that users with greater domain knowledge are better equipped to evaluate and utilise channel-related characteristics when assessing information usefulness.

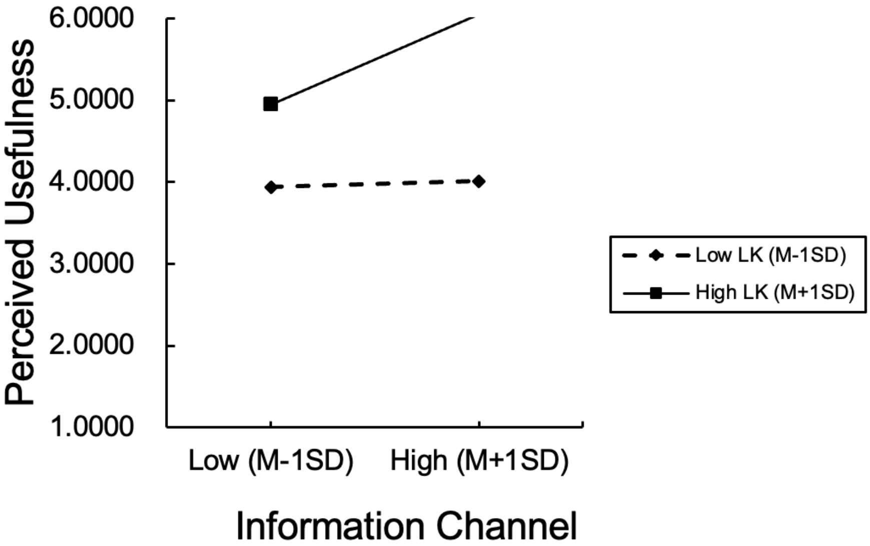

Figure 7.8: Moderation Effect of LK on the Relationship between 'IC and PU'

The significant moderation effect revealed in this analysis demonstrates that channel effectiveness in health information communication is strongly influenced by users' knowledge levels. The absence of channel effects at low knowledge levels, contrasted with strong effects at higher levels, suggests that channel optimisation strategies should be calibrated according to the target audience's domain expertise.

7.5.2.4 CI on 'PU→HIA'

The final moderation analysis investigated how cognitive involvement (CI) influences the relationship between perceived usefulness (PU) and health information adoption (HIA). Table 7.17 presents the results of this analysis using Process Model 1. The model demonstrated robust explanatory power with $R^2 = .440$, explaining approximately 44.0% of the variance in health information adoption. The overall model showed strong statistical significance ($F(3, 496) = 129.62$, $p < .001$), indicating its reliable predictive capability.

Variable	Coeff.	SE	t	p	LLCI	ULCI
Constant	4.9466	0.0498	99.3633	0.0000	4.8488	5.0444
PU	0.5189	0.0353	14.6890	0.0000	0.4495	0.5883
CI	0.2099	0.0421	4.9910	0.0000	0.1273	0.2926
PU × CI	0.1315	0.0285	4.6125	0.0000	0.0755	0.1875
$R^2 = 0.4395$, $F(3, 496) = 129.6174$, $p < 0.001$						

Table 7.17: Moderation Effect of CI on 'PU→HIA'

The analysis revealed significant main effects for both perceived usefulness ($\beta = .519$, $p < .001$) and cognitive involvement ($\beta = .210$, $p < .001$) on health information adoption. Notably, the interaction term between perceived usefulness and cognitive involvement (PU × CI) showed a significant positive effect ($\beta = .132$, $p < .001$). This significant interaction supports hypothesis H9, indicating that users' cognitive involvement levels meaningfully influence how perceived usefulness affects health information adoption.

To gain deeper insights into this moderating effect, the analysis examined the conditional effects of perceived usefulness on health information adoption at different levels of cognitive involvement, as shown in Table 7.18. The results revealed a consistent but strengthening pattern where the relationship between perceived usefulness and health information adoption becomes progressively stronger as cognitive involvement increases. At low cognitive involvement levels (-1 SD), whilst the relationship was significant ($\beta = .362$, $p < .001$), it was notably weaker than at higher levels. At mean cognitive involvement levels, the relationship strengthened considerably ($\beta = .519$, $p < .001$). The relationship was strongest at high cognitive involvement levels (+1 SD) ($\beta = .676$, $p < .001$), suggesting that users who are more cognitively engaged are more likely to translate their perceptions of usefulness into actual adoption behaviour.

LK	Effect	SE	t	p	LLCI	ULCI
-1.1971	0.3615	0.0539	6.7051	0.0000	0.2556	0.4675
0.0000	0.5189	0.0353	14.6890	0.0000	0.4495	0.5883
1.1971	0.6763	0.0438	15.4454	0.0000	0.5903	0.7623

Table 7.18: Conditional Effects of PU on HIA at Values of CI

Figure 7.9 provides a visual representation of this moderating effect, clearly illustrating how the relationship between perceived usefulness and health information adoption becomes stronger as cognitive involvement increases. The steeper slope at higher cognitive involvement levels indicates that the impact of perceived usefulness on adoption decisions is amplified when users are more cognitively engaged with the health information.

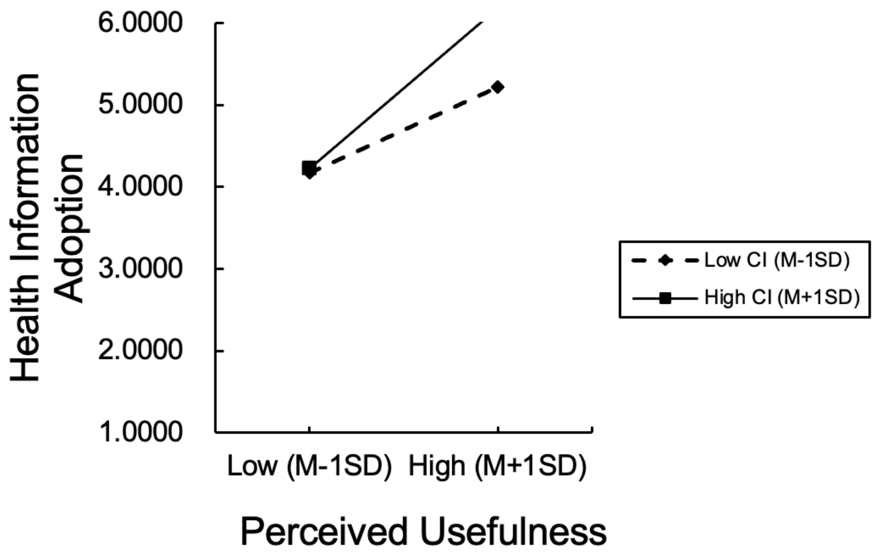

Figure 7.9: Moderation Effect of CI on the Relationship between 'PU and HIA'

The analysis reveals that cognitive involvement significantly enhances the relationship between perceived usefulness and health information adoption. This strengthening effect suggests that the likelihood of health information adoption increases substantially when users are more cognitively engaged with the content. The finding highlights the importance of user engagement in the health information adoption process, particularly in social media contexts where user attention and involvement can vary significantly.

7.5.3 Synthesis of Mediation and Moderation Effects

Based on the results of the mediation and moderation effects analyses, this study provides a comprehensive discussion of these two types of effects to fully explain the dissemination mechanisms of health information adoption on social media. By synthesising these effects, a complex social media health information adoption model is revealed, as shown in Figure 7.10.

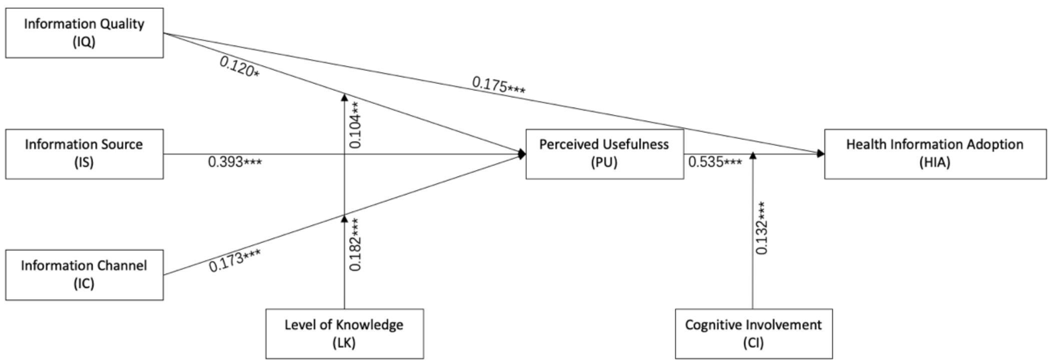

Figure 7.10: Social Media Health Information Adoption Model

At the core of this framework is the mediating role of perceived usefulness, which bridges the influence of information characteristics (quality, source, and channel) on adoption behaviour. The mediation analysis reveals that these information characteristics significantly affect perceived usefulness (H1, H2, H3), which strongly predicts health information adoption (H4). The nature of these mediation effects varies, with information quality showing partial mediation (H5), while source and channel effects are fully mediated by perceived usefulness (H6, H7). These findings highlight the crucial role of user perceptions in translating information characteristics into adoption decisions.

Building upon this mediation model, the moderation analysis identifies user knowledge and cognitive involvement as key boundary conditions. User knowledge significantly moderates the effects of information quality and channel on perceived usefulness (H8a, H8c), with stronger effects observed among high-knowledge users. Interestingly, the influence of information source on perceived usefulness remains consistent across knowledge levels (H8b). Furthermore, cognitive involvement moderates the relationship between perceived usefulness and adoption (H9), with highly involved users exhibiting a stronger link between usefulness perceptions and adoption behaviour.

In conclusion, this framework offers a comprehensive and subtle perspective on the complex mechanisms driving adoption decisions by integrating information characteristics, user perceptions, and individual differences.

7.6 Chapter Summary

This chapter validates the theoretical model and research hypotheses proposed in Chapter 6 through quantitative analysis. Firstly, descriptive statistical analysis shows that the sample has good representativeness, and the research variables basically conform to the normal distribution assumption. Subsequently, the reliability and validity analysis results show that the measurement model has good internal consistency, convergent validity, and discriminant validity, ensuring data quality. Structural equation model analysis validates the overall fit of the theoretical model and confirms the significant positive effects of information quality, information source, and information channel on perceived usefulness, as well as the significant positive effect of perceived usefulness on health information adoption. Mediation effect analysis reveals the key mediating role of perceived usefulness between information characteristics and health information adoption. Specifically, perceived usefulness plays a partial mediating role in information quality and health information adoption, as well as a full mediating role in information source and information channel and health information adoption. Moderation effect analysis shows that users' level of knowledge significantly moderates the effects of information quality and information channel on perceived usefulness, but its moderating effect on information source is not significant. Additionally, cognitive involvement significantly enhances the effect of perceived usefulness on health information adoption.

These research results not only validate most of the research hypotheses in Chapter 6 but also reveal the complex mechanisms of health information dissemination and adoption on social media. The findings highlight the central role of perceived usefulness in mediating the effects of information characteristics on adoption behaviour, as well as the significant moderating influence of individual user differences.

In the following chapter, the quantitative results of this study will be compared with the literature in Chapter 6, exploring similarities and differences with existing research. Additionally, the qualitative research findings from Chapter 5 will be integrated with the quantitative research results from this chapter, exploring how the two methods complement and validate each other. Finally, the methodological considerations and limitations of this study will be reflected upon.

Chapter 8 Discussion

8.1 Overview

This chapter first summarises the main findings of the research, then provides detailed explanations and discussions of these findings, comparing them with existing literature. Next, it explores the integration of qualitative and quantitative results, reflects on the research methods used, and points out the limitations of the study. This chapter lays the foundation for the conclusion and recommendations in Chapter 9.

8.2 Summary of Key Findings

This study explores the influencing factors and mechanisms of health-related information adoption on social media through a mixed-method design.

The qualitative research phase, through in-depth interviews and social media comment analysis, identifies six key factors: information quality factors, information source factors, information channel factors, recipient factors, perceived usefulness, and health information adoption. These findings provide the basis for constructing the theoretical model and designing quantitative research.

The quantitative research phase validates a comprehensive model that includes direct effects, mediating effects, and moderating effects through structural equation modelling and path analysis. The main findings are:

Direct effects: Information quality, information source, and information channel all significantly improve perceived usefulness, which in turn significantly improves health information adoption.

Mediating effects: Perceived usefulness partially mediates the relationship between information quality and health information adoption and fully mediates the relationships between information source and information channel with health information adoption.

Moderating effects: Level of knowledge significantly moderates the effects of information quality and information channel on perceived usefulness, but its moderating effect on information source is not significant. Cognitive involvement significantly moderates the effect of perceived usefulness on health information adoption.

These findings not only validate the research hypotheses but also reveal the complexity and multi-level nature of the health information adoption process on social media.

8.3 Interpretation and Comparison with Literature

The quantitative analysis reveals complex relationships among the constructs in the theoretical framework, with findings that both support and expand current theoretical understanding. The following interprets the results from direct effects (H1-H4), mediating effects (H5-H7), and moderating effects (H8a, H8b, H8c, H9), comparing the findings with existing literature while considering the specific context of social media health communication.

Direct Effects Analysis

The significant positive influence of information quality on perceived usefulness (supporting H1) aligns with the theoretical foundations established by Wang and Strong's (1996) multidimensional quality framework and extended by Wixom and Todd (2005), who bridged object-based beliefs (information quality) with behavioural beliefs (perceived usefulness). In social media environments, where users encounter vast amounts of health information, the strong relationship demonstrates that quality attributes remain fundamental in shaping utility assessments despite the absence of traditional gatekeeping mechanisms. This finding extends Sussman and Siegal's (2003) work on argument quality in their Information Adoption Model to the specific context of social media health information. The strength of this relationship likely stems from the high-stakes nature of health information, where quality assessment becomes particularly critical for users' decision-making processes, as suggested by Sillence et al.'s (2007) research on health information evaluation.

The significant positive impact of information source on perceived usefulness (supporting H2) confirms the theoretical relationship proposed in dual-process theories of persuasion, particularly the Elaboration Likelihood Model (Petty and Cacioppo, 1986). The findings suggest that source credibility remains important even in democratised social media environments, supporting Wathen and Burkell's (2002) assertion that source evaluation represents a fundamental component of information processing. This strong relationship indicates that users actively consider source attributes when evaluating information utility as a mechanism to manage information overload and misinformation risks. The findings also reflect Metzger et al.'s (2010) observation that social media environments introduce additional credibility indicators beyond traditional expertise and trustworthiness dimensions, suggesting users have adapted their source evaluation strategies to the networked nature of social media communication.

The significant positive impact of information channel characteristics on perceived usefulness (supporting H3) provides empirical support for Media Synchronicity Theory (Dennis et al., 2008), demonstrating how platform-specific features shape information processing and evaluation. This relationship is particularly noteworthy in light of Treem and Leonardi's (2013) identification of social media affordances (visibility, editability, persistence, and association) that influence information exchange and user perceptions. The strength of this relationship indicates that platform design and features play a more significant role in information evaluation than previously recognised in traditional communication models, supporting Rice's (1992) assertion that channel features can provide contextual cues that assist users in evaluating information relevance and applicability.

The significant positive relationship between perceived usefulness and health information adoption (supporting H4) aligns with the Technology Acceptance Model (Davis, 1989) while extending its application specifically to health information in social media contexts. This robust relationship supports Venkatesh et al.'s (2003) findings in the Unified Theory of Acceptance and Use of Technology, confirming that performance expectancy (perceived usefulness) serves as a strong predictor of behavioural intention across contexts. The strength of this relationship suggests that even in fast-paced social media environments, users' systematic assessment of information utility remains a crucial factor in adoption behaviour, consistent with Sussman and Siegal's (2003) Information Adoption Model positioning perceived usefulness as the direct antecedent to information adoption.

Mediating Effects Analysis

The partial mediation of perceived usefulness between information quality and health information adoption (supporting H5) supports and extends the theoretical foundations established by DeLone and McLean (2003) and Wixom and Todd (2005). This finding reveals a more complex relationship than initially theorised, suggesting that quality attributes influence adoption through two distinct pathways: directly and indirectly via utility perceptions. This dual-pathway effect is particularly relevant in social media environments where users often face rapid information processing demands. The direct effect might represent an immediate response to quality indicators, while the indirect effect through perceived usefulness likely represents a more deliberate evaluation process, where users systematically assess how quality attributes contribute to information utility. This finding aligns with Bhattacherjee and Sanford's (2006) research demonstrating that information characteristics affect adoption behaviours through their impact on users' cognitive assessments of information utility, while also suggesting that Eysenbach's (2007) framework of 'apomediaries' may apply to how quality assessments influence health information use in social media contexts.

The full mediation of perceived usefulness in the relationship between information source and health information adoption (supporting H6) provides strong support for dual-process theories of persuasion (Petty and Cacioppo, 1986) and extends Sussman and Siegal's (2003) Information Adoption Model. This complete mediation suggests that source credibility's influence on adoption works entirely through users' utility assessments rather than directly impacting adoption behaviour. This finding aligns with Hu and Sundar's (2010) research demonstrating that the influence of source credibility on health website evaluation was mediated by users' perceptions of the information's utility for health decision-making. The complete mediation indicates that social media users do not automatically adopt information from credible sources; instead, they process source credibility as part of their overall utility assessment, reflecting an adaptation to social media environments where source credibility alone may not suffice for adoption decisions.

Similarly, the full mediation of perceived usefulness between information channel and adoption (supporting H7) extends Media Synchronicity Theory (Dennis et al., 2008) to social media health communication. This complete mediation suggests that channel characteristics influence adoption behaviour solely through their impact on perceived utility rather than directly affecting adoption decisions. This finding aligns with Lu et al.'s (2005) research demonstrating that channel features influenced adoption intentions primarily through perceived usefulness. The complete mediation might reflect users' growing ability to evaluate how platform characteristics contribute to information value rather than being directly influenced by platform features, supporting Treem and Leonardi's (2013) work on how social media affordances shape information exchange and user perceptions.

Moderating Effects Analysis

The significant positive moderating effect of knowledge level on the relationship between information quality and perceived usefulness (supporting H8a) provides strong support for the Elaboration Likelihood Model (Petty and Cacioppo, 1986) and Heuristic-Systematic Model (Chaiken, 1980). This finding suggests that users with higher knowledge levels are better able to evaluate information quality, leading to stronger quality-utility relationships. This moderation effect aligns with Grewal et al.'s (1994) research demonstrating that domain knowledge moderated the relationship between argument quality and message evaluation, with high-knowledge individuals showing greater sensitivity to quality variations. The strength of this moderating effect suggests that knowledge level plays a key role in determining how quality attributes are translated into utility assessments, particularly relevant in health information contexts where technical complexity can vary significantly.

The non-significant moderating effect of knowledge level on the relationship between information source and perceived usefulness (not supporting H8b) challenges traditional theoretical assumptions about how expertise influences source evaluation. This unexpected finding becomes more understandable when considered within the unique context of social media health communication. While Winter and Krämer (2012) found that domain expertise moderated the influence of source credibility on information evaluation, our results suggest this relationship may be more complex in social media environments. The non-significant moderation suggests that high knowledge levels may not necessarily enhance users' ability to translate source credibility into utility assessments in these environments. This could be because both high and low knowledge users increasingly rely on collective wisdom and social validation processes rather than traditional authority markers when evaluating sources on social media, reflecting Metzger et al.'s (2010) observation that social media environments introduce expanded conceptualisations of source factors including similarity, familiarity, and social validation.

The significant positive moderating effect of knowledge level on the channel-usefulness relationship (supporting H8c) extends Media Synchronicity Theory (Dennis et al., 2008) in important ways. This significant moderation aligns with Spence and Moinpour's (1972) finding that expertise moderated individuals' responses to communication channel characteristics. The positive moderation suggests that knowledgeable users may be better at leveraging social media platform features to enhance their information evaluation processes, reflecting a greater ability to navigate platform affordances effectively and derive more utility from platform-specific features such as interactive elements, social validation mechanisms, and information organisation tools.

The significant positive moderating effect of cognitive involvement on the usefulness-adoption relationship (supporting H9) aligns with the Elaboration Likelihood Model (Petty and Cacioppo, 1986) and extends Zaichkowsky's (1985) conceptualisation of involvement. This moderation effect supports Celsi and Olson's (1988) research demonstrating that involvement moderated the relationship between cognitive elaboration and behavioural responses, as well as Bhattacherjee and Sanford's (2006) finding that job relevance moderated the influence of perceived usefulness on acceptance attitudes. The strength of this moderating effect suggests that cognitive involvement serves as a key amplifier in the utility-adoption relationship, reflecting Park and Lee's (2008) observation that involvement with health issues moderated consumers' responses to online health information, with higher involvement strengthening the relationship between evaluative judgments and behavioural intentions.

8.4 Integration of Qualitative Findings and Quantitative Results

The results of the qualitative and quantitative research show high consistency in multiple aspects while also providing complementary insights. This integration not only enhances the reliability of the research findings but also deepens the understanding of the health information adoption process on social media.

Firstly, the six main constructs identified in the qualitative research were validated in the quantitative research. The concepts of information quality, information source, information channel, recipient factors, perceived usefulness, and health information adoption extracted through interviews and comment analysis in the qualitative phase were successfully transformed into measurable variables in the quantitative research. This transformation not only ensures the coherence of the research but also enhances the ecological validity of the quantitative model.

Secondly, the relationships between factors found in the qualitative research were further refined and validated in the quantitative analysis. For example, qualitative research indicates that information characteristics (quality, source, channel) may influence adoption behaviour by affecting users' evaluation of information. This observation was concretised in the quantitative research as the mediating role of perceived usefulness and received statistical support. In particular, the quantitative results showing the partial mediating effect of information quality on health information adoption are consistent with the direct and indirect influences of information quality observed in the qualitative research.

The complexity of recipient factors was reflected in both research phases. The qualitative research initially divided recipient factors into knowledge and ability aspects as well as attitude and emotional aspects. This insight was operationalised in the quantitative research as two moderating variables: level of knowledge and cognitive involvement. The quantitative results validated the moderating effects of these two variables, deepening the understanding of the role of individual differences in the information adoption process.

However, there are also some differences between qualitative and quantitative research. In the qualitative research, some participants emphasised factors such as cultural sensitivity, privacy concerns, and moral considerations, which were not directly included in the quantitative model. This difference reflects the value of mixed methods research, where qualitative methods can capture more subtle and contextualised factors, while quantitative methods provide a more universally applicable model.

Furthermore, the qualitative research provided background information for understanding the quantitative results. For example, the quantitative research found that the moderating effect of the level of knowledge on the relationship between information source and perceived usefulness was not significant. This result can be explained by reviewing the qualitative data. The qualitative research suggested that the influence of information source may depend more on social cognition and trust mechanisms rather than personal level of knowledge.

Overall, the integration of qualitative and quantitative results provides a more comprehensive and in-depth picture of the health information adoption process on social media. The qualitative research provided the foundation and direction for model construction, while the quantitative research validated and refined these relationships.

8.5 Methodological Considerations

This study employs an exploratory sequential mixed methods design to comprehensively and deeply explore the complex phenomenon of health information adoption on social media. This approach combines the strengths of qualitative and quantitative research but also faces some methodological challenges.

The qualitative phase employed a combination of in-depth interviews and extensive social media comment analysis. This triangulation strategy enhances the comprehensiveness and credibility of the research. In-depth interviews allow for deep exploration of individual attitudes, motivations, and experiences, while comment analysis provides larger-scale, more natural user behaviour data. However, qualitative research also has some limitations. The sample size of 12 interviewees is still relatively small compared to the vast population of social media users. Additionally, qualitative data analysis may be influenced by the researcher’s subjective judgments, and qualitative findings may be difficult to directly generalise to larger populations.

The quantitative phase used a structured questionnaire containing 42 measurement items covering seven main constructs. This method allows for standardised measurement of a large sample, enhancing the statistical power and generalisability of the results. However, quantitative research also faces some challenges. While 500 participants meet basic statistical requirements, it is still insufficient relative to the total population of social media users. Due to the use of an online questionnaire survey, the sample may be biased towards users who are more familiar with social media and the internet, potentially not fully representing all social groups, especially the elderly or groups that use the internet less. Self-reported measures may be subject to social desirability bias and common method bias. Furthermore, although mature scales were referenced, the measurement tools may still not fully capture all relevant factors in the dynamic social media environment.

A significant methodological consideration pertains to sample representativeness. The quantitative sample demonstrates notable demographic skewing, with 72.8% of participants under 35 years old and 75.2% possessing bachelor's degrees or higher. Similarly, the qualitative phase predominantly captured perspectives from educated professionals. This demographic profile, whilst consistent with active social media users, creates a substantial discrepancy between the research sample and China's broader population. Upon reflection, this distribution is not merely a methodological limitation but potentially reflects the actual demographic pattern of active health information consumers on Chinese social media platforms. The qualitative sample was intentionally designed to include diverse occupational backgrounds (healthcare professionals, media practitioners, academics, and general public) rather than focusing on age or educational diversity, as professional perspective was considered more relevant to understanding health information adoption mechanisms. For the quantitative phase, the self-selection of participants interested in health information research likely mirrors the self-selection that occurs naturally in health information engagement on social media. Rather than artificially balancing demographics to match broader population statistics, this approach captures authentic patterns of engagement. Nevertheless, this means the study primarily reflects health information adoption patterns amongst younger, educated social media users rather than the general Chinese population. This limitation affects the ecological validity of the findings, particularly regarding their applicability to older citizens and those with lower educational attainment, who may have distinct information evaluation approaches but represent significant segments of China's population. Future research might benefit from targeted sampling strategies to specifically investigate these underrepresented groups, though the challenges in recruiting participants who are less engaged with both social media and health information.

In terms of data analysis, this study uses Structural Equation Modelling (SEM) and SPSS Process Macro for mediation and moderation effect analysis. These advanced statistical methods allow for the simultaneous examination of complex direct, indirect, and conditional effects, enhancing the rigour of the research. However, these methods also have their limitations. SEM assumes linear relationships between variables, potentially overlooking potential non-linear relationships. Additionally, multiple moderation or mediation-moderation combination effects may not have been considered.

In conclusion, the methodological choices in this study show significant advantages in exploring the complex phenomenon of health information adoption on social media. By combining qualitative and quantitative methods, the study not only provides descriptive insights but also establishes a testable theoretical model. However, researcher also need to be aware of the limitations of each method and remain cautious when interpreting results.

8.6 Limitations of the Study

Despite the methodological rigour maintained throughout this study, there are still some limitations that need to be considered when interpreting results and applying findings.

Limitations in Cross-cultural Applicability

The sample in this study mainly comes from China, while the theoretical framework and most measurement tools originate from Western literature. This difference in cultural background may make it difficult to generalise the research results directly to other cultural contexts. China’s unique social media ecosystem (such as WeChat, Douyin, and Weibo) differs significantly from Western platforms (such as Facebook, Twitter, and TikTok) regarding usage patterns and information dissemination mechanisms. Moreover, the collectivist tendencies in Chinese culture, attitudes towards authority, and health concepts may differ from Western individualistic cultures, which may affect how users process and adopt health information. Future research should consider conducting cross-cultural comparisons to validate the model's applicability in different cultural contexts.

Sample Representativeness Limitations

The sample composition presents particular challenges for generalisation to the broader Chinese population. The sample demonstrates pronounced skewing towards younger participants and those with higher educational qualifications. This demographic distribution diverges significantly from China's overall population structure, particularly underrepresenting older citizens who comprise an increasing proportion of both the general population and social media users. The relative absence of perspectives from older and less educated groups represents a notable limitation, especially considering that these demographics may have different health information needs, technological literacy levels, and information evaluation approaches. Consequently, the findings primarily reflect the health information adoption patterns of younger, educated social media users rather than the general Chinese population.

Complexity of the Social Media Environment

There is considerable information noise on social media platforms, and users may face information overload problems. This environment may reduce users' sensitivity to information characteristics, weakening the role of certain factors in traditional information adoption models. For example, in an environment where information flows rapidly, users may rely more on intuitive judgments or the collective wisdom of social networks rather than carefully evaluating the quality and source of each piece of information. This study may not have fully captured this social media-specific information processing pattern.

Assessment of Dynamics and Long-term Effects

The research mainly focuses on the immediate impact of information adoption and fails to track the long-term effects and actual behavioural changes of health information adoption. Health behaviour change is usually a long-term process and a single instance of information adoption may not fully reflect the complexity of this process. Moreover, the social media environment and health information dissemination landscape are rapidly changing. The cross-sectional design of this study may not capture these dynamic changes. Additionally, emerging social media platforms (such as Douyin) may bring new information dissemination patterns, affecting users' information adoption behaviour. A longitudinal research design might be more suitable for capturing these dynamic changes.

Types of Health Information and Contextual Factors

The study fails to fully distinguish between different types of health information (such as preventive information, treatment information, chronic disease management information, etc.) and different health contexts (such as emergency public health events vs daily health management). These different types of information may have different adoption mechanisms and influencing factors.

Social Media Platform Characteristics

Different social media platforms (such as WeChat, Douyin, and Weibo) differ in functional design, user groups, and information dissemination mechanisms. This study fails to fully explore the impact of these platform differences on health information adoption. In particular, the short video format of some emerging platforms (Douyin) may bring entirely new patterns of health information dissemination and adoption.

Individual Differences and Psychological Factors

Although the study considers the level of knowledge and cognitive involvement, other important individual differences and psychological factors, such as health beliefs, risk perception, emotional states, etc., may not be included in the model. These factors may have significant impacts on the processing and adoption of health information.

8.7 Chapter Summary

This chapter comprehensively discusses the main findings of the research, integrating qualitative insights and quantitative results and systematically comparing them with existing literature to provide an in-depth interpretation of the complex mechanisms of health information adoption on social media. These findings not only validate some existing theories but also extend the understanding of the unique characteristics of health information dissemination in social media environments. In particular, the reasons why the hypothesis regarding the moderating effect of level of knowledge on the relationship between information source and perceived usefulness was not supported, an unexpected finding that challenges some existing theories while providing new directions for future research. The methodological considerations discuss in detail the application of mixed method design in this study, including the integration of qualitative and quantitative methods, sample selection strategies, and measurement tool design. The discussion of research limitations covers aspects such as sample representativeness, cross-cultural applicability, and long-term effect assessment. The discussion in this chapter establishing a bridge from research findings to practical applications. Chapter 9 will revisit the research objectives and questions, synthesise key findings, and elaborate on theoretical contributions and practical implications. Furthermore, the research limitations discussed in this chapter directly guide the exploration of future research directions in Chapter 9.

Chapter 9 Conclusion and Recommendations

9.1 Revisiting Research Objectives and Questions

This study focuses on the dissemination mechanisms of health-related misinformation on social media and strategies for its governance and management. It sets four interrelated and progressive research objectives, forming a systematic research framework:

1. To explore factors influencing the adoption of health-related information on social media. This objective lays the foundation for subsequent research, using qualitative research methods to delve into the complexity of how users process health information in the Chinese social media environment.

2. To construct a theoretical framework of factors influencing the adoption of health-related information on social media, integrating traditional information adoption theories while considering the unique characteristics of the social media environment. This theoretical model provides a framework for the subsequent quantitative investigation.

3. To examine the perception pathways of social media users in the process of adopting health-related information. The theoretical model is validated and refined through quantitative research methods, exploring the complex relationships among various influencing factors.

4. To propose governance and strategies recommendations for the management of health-related misinformation on social media, translating theoretical findings into practical guidance.

To achieve these objectives, the study addresses three core research questions that closely correspond to the research objectives, reflecting the research logic of the exploratory sequential mixed methods:

1. Qualitative Research Question: What are the key factors influencing the adoption of health-related information on social media? This question corresponds to the first research objective, explored through in-depth interviews and social media comment analysis, laying the foundation for subsequent quantitative research.

2. Quantitative Research Question: How do the identified influencing factors specifically affect the adoption pathways of health-related information on social media? This question aligns with the second and third research objectives, quantifying the degree of influence and mechanisms of various factors through large scale questionnaire surveys and advanced statistical analysis, validating and refining the theoretical model.

3. Comprehensive Research Question: How can the effective dissemination of accurate health information be enhanced while reducing the spread of misinformation on social media? This question addresses the fourth research objective, integrating findings from both qualitative and quantitative research to propose balanced and effective governance strategies.

This study employs exploratory sequential mixed methods, ensuring the reliability and validity of the findings. By addressing these research objectives and questions, this study not only deepens the understanding of health information dissemination mechanisms on social media but also provides a theoretical basis and practical guidance for addressing the significant challenge of health misinformation.

9.2 Synthesis of Key Findings

This study employs an exploratory sequential mixed methods to comprehensively investigate the dissemination mechanisms of health-related misinformation on social media. The research findings can be synthesised from four key aspects:

Qualitative Research Findings

The qualitative phase of the research, through in-depth interviews and social media comment analysis, revealed three core external factors affecting users' perceived usefulness of health information: information quality, information source, and information channel. These findings mainly highlight the importance of information characteristics in the social media environment, where the prevalence of misinformation has made users increasingly concerned.

The analysis also identified two significant internal factors: users' level of knowledge and cognitive involvement. These individual factors were found to play crucial moderating roles in information processing. This finding emphasises the importance of individual differences in health information adoption, suggesting that personal characteristics significantly influence how users evaluate and process health information on social media platforms.

Quantitative Research Results

The quantitative phase validated a comprehensive theoretical framework containing seven latent variables through Structural Equation Modelling and path analysis of data from 500 survey respondents. It is important to contextualise these quantitative results within the demographic characteristics of the sample. As detailed in 7.2.1, the survey respondents were predominantly younger (72.8% under 35 years) and highly educated (75.2% with bachelor's degrees or higher), which diverges from China's broader population structure. This demographic composition means the statistical relationships identified primarily reflect patterns amongst younger, educated social media users rather than the general Chinese population. With this contextual understanding, the quantitative results can be categorised into three distinct effects:

Direct Effects:

Information quality showed a significant positive effect on perceived usefulness ($\beta = 0.120$, $p = 0.040$).

Information source demonstrated a strong positive influence ($\beta = 0.393$, $p < 0.001$).

Information channel exhibited a significant positive impact ($\beta = 0.173$, $p < 0.001$).

Perceived usefulness strongly influenced health information adoption ($\beta = 0.535$, $p < 0.001$).

Mediating Effects:

Information quality showed a partial mediating effect through perceived usefulness ($\beta = 0.071$, $p = 0.094$, 95% CI: -0.120~0.158).

Information source demonstrated a full mediating effect ($\beta = 0.252$, $p = 0.001$, 95% CI: 0.144~0.399).

Information channel exhibited a full mediating effect ($\beta = 0.107$, $p = 0.003$, 95% CI: 0.040~0.183).

Moderating Effects:

Level of knowledge significantly moderated the effects of information quality ($\beta = 0.1040$, $p < 0.01$) and information channel ($\beta = 0.1819$, $p < 0.001$).

The moderating effect on information source was not significant ($\beta = -0.0492$, $p > 0.05$).

Cognitive involvement significantly moderated the effect of perceived usefulness on health information adoption ($\beta = 0.1315$, $p < 0.001$).

These results collectively construct a multi-level, dynamic model of health information adoption on social media, revealing the complex interactions among information characteristics, user characteristics, and information processing processes.

Unexpected Research Insights

The study revealed several unexpected findings that provide valuable insights into health information dissemination mechanisms on social media:

The most notable unexpected finding was the non-significant moderating effect of knowledge level on the relationship between information source and perceived usefulness ($\beta = -0.0492$, $p > 0.05$). This finding challenges traditional theoretical assumptions about how expertise influences information evaluation. The qualitative data suggests this may be due to the unique characteristics of social media environments, where users across different knowledge levels tend to rely more on collective wisdom and social proof rather than traditional authority markers.

Another unexpected finding was the stronger-than-anticipated influence of information channel characteristics on perceived usefulness ($\beta = 0.173$, $p < 0.001$), exceeding the direct effect of information quality ($\beta = 0.120$, $p = 0.040$). This suggests that in the social media environment, platform-specific features play a more crucial role in information adoption than previously theorised. This finding is supported by interview data highlighting how platform characteristics shape information reception and processing.

The study also revealed unexpected complexity in the mediation patterns, with information source and channel showing complete mediation through perceived usefulness, while information quality demonstrated only partial mediation. This suggests different mechanisms at work for different types of information characteristics, highlighting the complex nature of health information processing in social media environments.

These unexpected findings collectively suggest the need for refined theoretical models specific to social media health communication, particularly considering how traditional theories of information processing and adoption may need modification when applied to social media contexts.

Integration of Qualitative and Quantitative Results

The integration of qualitative findings and quantitative results demonstrates both consistency and complementarity in understanding health information dissemination on social media platforms.

The six key constructs identified in the qualitative phase (information quality factors, information source factors, information channel factors, perceived usefulness, health information adoption, and recipient factors) were further developed in the quantitative phase. The recipient factors were specifically refined into two distinct moderating variables (level of knowledge and cognitive involvement), resulting in the seven-construct theoretical model that was validated through structural equation modelling.

The qualitative insights provided valuable context for understanding the quantitative results, particularly regarding the relationships between information characteristics and perceived usefulness. The quantitative analysis further validated these relationships through statistical testing, confirming the significance of both direct and indirect effects through the mediating role of perceived usefulness.

While the qualitative phase also identified additional contextual categories related to personal, professional, and social factors, these were treated as contextual conditions rather than core theoretical components. These contextual insights, though not directly measured in the quantitative model, provided valuable background for understanding the broader social dynamics affecting information dissemination and adoption patterns and informing the development of governance strategies for managing health-related misinformation.

The integration of both methodological approaches has provided a more comprehensive understanding of how users process and adopt health information on social media, offering both theoretical depth and practical insights for addressing health misinformation challenges. However, this integrated understanding should be interpreted with recognition of the research's demographic limitations. Both qualitative and quantitative phases predominantly captured perspectives and patterns from younger, educated participants, potentially underrepresenting health information behaviours specific to older or less educated social media users.

9.3 Theoretical Contributions

This study not only verifies and applies existing theoretical frameworks but, more importantly, provides several original contributions that extend beyond established knowledge boundaries through its exploratory mixed-methods design. Firstly, whilst information adoption models have been extensively researched in Western contexts, this study extends them to the Chinese social media environment, considering the unique sociocultural dynamics and platform characteristics of this setting, filling a significant gap in cross-cultural application. Secondly, through in-depth qualitative research, this study identifies platform-specific influence mechanisms not fully captured by traditional information adoption theories, particularly factors such as content display algorithms, community interaction features, and platform reputation systems, which are often simplified in existing literature. Thirdly, the quantitative research reveals a differentiated pattern of knowledge-level moderation effects—significantly moderating the influence of information quality and information channels on perceived usefulness, but not significant for information sources—challenging conventional theoretical assumptions about the uniformity of expertise influence. Fourthly, through mixed methods, this research explores the multidimensional nature of 'perceived usefulness' in health information contexts, transcending the relatively simplified definition in technology acceptance models. Finally, the governance framework proposed by this study integrates multi-level, multi-stakeholder perspectives, providing a new approach to health misinformation governance with both theoretical depth and practical applicability. These contributions collectively advance health information adoption theory in the digital age and lay the foundation for future cross-cultural, cross-platform research.

Extension of Health Information Adoption Theory

This study constructs a more comprehensive social media health information adoption model by integrating the Information Adoption Model (IAM) and Technology Acceptance Model (TAM). The innovation of this model is reflected in its environment-specific nature, multi-dimensional integration, and dynamic process view. The model particularly considers the unique attributes of the social media environment, such as information overload, rapid dissemination, and user-generated content, filling theoretical gaps in traditional information adoption theories in the digital, social communication environment. By incorporating user characteristics (level of knowledge, cognitive involvement) as moderating variables, the model reflects the multi-level nature of the health information adoption process. The introduction of perceived usefulness as a mediating variable captures the dynamic process from information exposure to final adoption, providing a more complete theoretical framework.

Revelation of Social Media-Specific Mechanisms

The research findings challenge some assumptions of traditional information adoption theories, revealing unique information-processing mechanisms in the social media environment. In particular, the study found that the level of knowledge does not significantly moderate the effect of information source on perceived usefulness, suggesting that in the social media environment, traditional expert authority may give way to more complex trust mechanisms, such as social proof and word-of-mouth effects. Furthermore, the study emphasises the key role of social media platform characteristics in information dissemination, extending the understanding of communication channels in traditional theories and highlighting the importance of technological platforms in shaping users' information experience.

Deepening of the Concept of Perceived Usefulness

This study enriches the understanding of the role of perceived usefulness in the health information adoption process. The research confirms perceived usefulness as a key mediating variable connecting information characteristics and adoption behaviour, deepening the understanding of how users evaluate and process health information. At the same time, the study finds that perceived usefulness plays different degrees of mediating roles between different information characteristics (quality, source, channel) and adoption behaviour, providing a new perspective for understanding the complexity of health information processing.

Theoretical Integration of Recipient Characteristics

By incorporating user level of knowledge and cognitive involvement as moderating variables into the model, this study emphasises the key role of user characteristics in the information processing process. This finding challenges the ‘one-size-fits-all’ information dissemination strategy, providing a theoretical basis for personalised health communication. The study also explores the interaction between user characteristics and information characteristics, enriching the understanding of the complexity of the health information adoption process.

Contributions to Misinformation Dissemination Theory

This study provides new theoretical perspectives for understanding the dissemination mechanisms of health-related misinformation on social media. By analysing various factors influencing health information adoption, the research indirectly reveals potential mechanisms for the rapid spread of misinformation utilising social media characteristics. The research results suggest how users evaluate and potentially resist misinformation, providing a basis for constructing misinformation defence theories. Additionally, the study emphasises the interaction of information quality, source credibility, dissemination channels, and user characteristics in the health information ecosystem, providing a systematic framework for understanding and managing misinformation.

In summary, this study not only expands the theoretical boundaries of health information adoption but also provides new theoretical perspectives for understanding health information dissemination in the social media environment, especially the dissemination mechanisms of misinformation. These contributions lay a theoretical foundation for practical interventions and have significant implications for addressing the challenges of health information dissemination in the digital age.

9.4 Practical Implications and Governance Strategies

The theoretical findings and empirical results of this study provide important insights for addressing the challenges of the spread of health-related misinformation on social media. Based on the findings and results, it proposes a series of targeted governance strategies aiming to facilitate the effective dissemination of accurate health information while curbing the spread of misinformation. These strategies consider multiple dimensions, including information characteristics, user attributes, platform mechanisms, and policies and regulations, thus providing a comprehensive and systematic solution. Importantly, the implementation of these strategies must acknowledge the demographic limitations of the research sample. As detailed in 7.2.1, study participants were predominantly younger and highly educated, representing a specific subset of Chinese social media users rather than the general population. This demographic profile has significant implications for governance strategies, as different age groups and educational backgrounds may exhibit distinct patterns of health information processing and adoption. Therefore, the following recommendations include specific considerations for adapting interventions to demographic groups underrepresented in this study, ensuring more inclusive and effective governance approaches.

The governance strategies and recommendations presented herein derive directly from the empirical findings of this research, particularly the qualitative analysis in Chapter 5 and the quantitative results in Chapter 7. Each recommendation addresses specific influence mechanisms identified in the study, aiming to strengthen positive factors that promote health information adoption whilst mitigating negative factors that contribute to misinformation dissemination. These recommendations also consider the specific feedback from interview participants and user preferences revealed in the questionnaire survey, ensuring the practicality and acceptability of the strategies. Through this evidence-based approach, the theoretical insights gained from this research are systematically translated into actionable solutions for addressing the challenges of health-related misinformation on social media.

9.4.1 Enhancing Information Quality and Credibility

The results in Chapter 7 show that information quality has both direct and indirect influences on health information adoption. The quantitative analysis indicates that information quality has a significant positive impact on perceived usefulness ($\beta = 0.120$, $p = 0.040$), and it also maintains a direct significant positive influence on health information adoption ($\beta = 0.175$, $p = 0.001$). This implies that improving the quality and credibility of health information should be a primary strategy for curbing the spread of misinformation. Based on this result, the study proposes the following recommendations:

Establishing a Health Information Quality Assessment System

Relevant authorities should collaborate with medical experts, communication scholars, and technical specialists to develop a set of health information quality assessment standards applicable to the social media environment. This set of standards should include dimensions such as accuracy, timeliness, completeness, and readability. As Professor F mentioned in the interview, "*We need a unified standard to evaluate the quality of health information on social media, which should consider both professionalism and public comprehensibility.*"

Moreover, automated tools can be developed, utilising natural language processing and machine learning technologies, to conduct real-time quality assessments of health information on social media. Multiple interviewees support this recommendation, as

Researcher E pointed out: "*Artificial intelligence technology has great potential in information screening and assessment, and we should fully utilise these technologies to improve the quality of health information.*"

Strengthening the Participation of Professional Institutions and Experts

Encourage medical institutions, public health departments, and relevant experts to actively participate in the dissemination of health information on social media. Official certified accounts can be established to regularly publish authoritative health information and provide timely responses and clarifications on popular health topics. As Doctor A emphasised in the interview, "*As healthcare professionals, we are responsible for speaking up on social media and providing accurate and reliable health information to the public.*"

An expert database system should also be established to provide social media platforms with rapid query and verification services. As News Editor C suggested, "*We can build a cross-disciplinary expert database so that when there is controversial health information, we can quickly contact relevant experts for verification and explanation.*"

Implementing an Information Traceability Mechanism

The research findings support the implementation of a health information traceability mechanism on social media platforms. The quantitative analysis demonstrates that information source significantly influences health information adoption through perceived usefulness ($\beta = 0.252$, $p = 0.001$), highlighting the critical role of source credibility in users' decision-making processes. As Social Media Influencer D noted in the interviews: "*Information traceability is important for us content creators, as it not only enhances our credibility but also helps the audience assess the reliability of the information.*"

This mechanism would be implemented through a three-tiered approach:

Firstly, at the platform level, social media companies would integrate source verification tools directly into their publishing interfaces. Content creators sharing health information would be required to include metadata on the information source, categorised as: (1) professional medical literature with citation details, (2) official health authority announcements with dated references, (3) expert opinion with professional credentials, or (4) personal experience with appropriate disclaimers. This classification system would be presented as a simple, mandatory field during content creation, minimising burden whilst maximising compliance.

Secondly, at the regulatory level, the National Health Commission, working jointly with the Cyberspace Administration of China, would establish unified standards for health information source attribution. These agencies would provide a regularly updated database of authoritative health sources accessible to all platforms, allowing for automated verification of cited sources. This regulatory framework would be integrated with existing content management systems rather than creating entirely new structures, enhancing feasibility and reducing implementation barriers.

Thirdly, at the user level, platforms would develop intuitive visual indicators, such as colour-coded badges or source information buttons that immediately signal source reliability to users. These indicators would be accompanied by one-click access to original sources and simplified explanation of source credibility assessment, addressing the finding that cognitive involvement significantly moderates information adoption ($\beta = 0.1315$, $p < 0.001$).

The responsibility allocation would be clearly defined: social media platforms would be responsible for technical implementation and day-to-day monitoring; health authorities would provide authoritative source databases and verification standards; content creators would comply with source attribution requirements; and users would participate through reporting inaccurately sourced information. This multi-stakeholder approach directly addresses the interview findings that emphasised the need for collaborative governance with clearly defined responsibilities.

This mechanism would not only enhance information credibility but would also create a culture of accountability in health information sharing, reducing the likelihood of misinformation propagation whilst facilitating the dissemination of accurate health information. As University Student H emphasised in the interviews: "*If there were a simple tool that could help us quickly verify the source and reliability of health information, it would greatly improve our ability to discern information.*"

Establishing a Health Information Certification System

It is recommended that relevant authorities collaborate with social media platforms to establish a health information certification system. Health information verified by professional institutions or experts can be awarded a 'certification mark' to enhance its credibility. This system can adopt a tiered certification mechanism, implementing different levels of certification processes based on the importance and impact range of the information. As Nurse B pointed out, "*An authoritative certification system can greatly increase our trust in health information, especially for important health warnings and medical advice.*"

These information quality enhancement strategies must consider varying information evaluation capabilities across different demographic groups. While the current study findings primarily reflect patterns observed among younger, educated participants, implementation should address the needs of older and less educated users who may assess information quality through different criteria. For instance, older users may place greater emphasis on traditional authority markers, while those with lower educational attainment might rely more heavily on accessibility and comprehensibility. Quality assessment systems and certification mechanisms should therefore incorporate differentiated approaches to reach diverse user segments effectively.

The health information quality assessment system proposed in this study is primarily designed for the Chinese social media environment, considering China's specific regulatory framework, healthcare system, and social media ecosystem. However, its core principles could be adaptively applied to global contexts, providing a reference framework whilst respecting cultural and regulatory differences across countries.

It is worth noting that several pre-existing health information quality assessment systems have been established internationally. The most prominent example is the Health On the Net Foundation Code of Conduct (HON Code), established in the early 2000s, which outlines eight core principles including authoritative, complementarity, privacy, attribution, justifiability, transparency, financial disclosure, and advertising policy (Boyer et al., 2011). The HON Code provides quality certification for websites and has become a globally recognised standard for health information quality.

The assessment system recommended in this study draws upon the strengths of these existing frameworks whilst innovating for the unique characteristics of social media environments, particularly considering factors such as the ephemeral nature of health information on social media, the predominance of user-generated content, and the influence of algorithmic recommendation systems. By integrating international best practices and adapting to China's specific needs, this system aims to provide a more suitable quality assessment mechanism for the dynamic social media environment.

9.4.2 Improving Users' Health Literacy and Critical Thinking Skills

The results in Chapter 7 indicate that users' level of knowledge and cognitive involvement play important moderating roles in the process of health information processing. The quantitative analysis shows that the level of knowledge significantly moderates the impact of information quality on perceived usefulness ($\beta = 0.1040$, $p < 0.01$), and cognitive involvement significantly enhances the influence of perceived usefulness on the health information adoption ($\beta = 0.1315$, $p < 0.001$). Therefore, improving users' health literacy and critical thinking skills is crucial for resisting misinformation. Based on these findings, the study proposes the following recommendations:

Implementing Targeted Health Education Programmes

Design and implement health education programmes explicitly differentiated for diverse demographic segments, with particular attention to groups underrepresented in this study—notably older adults and those with lower educational attainment. The research findings indicate that level of knowledge significantly moderates information quality assessment ($\beta = 0.1040$, $p < 0.01$), suggesting that educational interventions must be calibrated to different baseline knowledge levels. Programmes for older adults should emphasise bridging digital literacy gaps alongside health content, potentially utilising more traditional communication channels as entry points to digital health information. For less educated populations, programmes should focus on developing fundamental critical assessment skills using accessible language and relatable contexts. As Retiree J stated despite limited representation of this demographic: "*We older adults also need this kind of education, especially training on how to discern true and false health information on the internet.*" These programmes should comprehensively address basic health knowledge, common disease prevention, and tailored information evaluation techniques appropriate to each group's specific needs and capabilities.

The interactive and easily shareable features of social media platforms can be utilised to develop educational content, such as short videos and illustrated popular science articles. As fitness coach K suggested, "*We can produce some interesting health science videos, which can not only spread correct health knowledge but also attract the attention of young people.*"

Cultivating Public Media Literacy

Incorporate media literacy education into school curricula and conduct media literacy training for the general public. The focus should be on cultivating the public's critical thinking skills in information, including how to identify the reliability of information sources, cross-check information, and recognise false or misleading content. As Professor F emphasised, "*Media literacy education should start from primary school so that children can develop the ability to discern information from an early age.*"

Case studies and simulation exercises can be used to enhance practical skills. As Civil Servant I suggested, "*We can organise some workshops that simulate social media environments, allowing participants to practise how to identify and respond to various types of health misinformation.*"

Developing Health Information Evaluation Guidelines

Compile health information evaluation guidelines for ordinary users, providing simple and practical methods to help users assess the reliability of health information. The guidelines can include steps such as checking the source of information, finding scientific evidence, and comparing it with official information. As Housewife L expressed, "*As a non-professional, I really need such guidelines to help me judge whether the health information on the internet is reliable.*"

Encourage social media platforms to proactively push these evaluation guidelines to users when they are browsing health information. As Social Media Influencer D suggested, "*The platform can set an 'information evaluation guide' button next to health-related content so that users can obtain recommendations on how to assess the reliability of the information by clicking on it.*"

Developing Interactive Learning Tools

Utilise artificial intelligence technology to develop smart interactive learning tools to help users improve their health information identification capabilities. These tools can simulate real social media environments, provide various types of health information for users to judge, and give immediate feedback and explanations. As Researcher E pointed out, "*We can develop a 'health information identification game', allowing* *users to learn how to discern different types of health information in a game-like manner, which is both engaging and effective.*"

Through continuous learning and practice, users can gradually improve their judgment abilities. As University Student H stated, "*If there were such learning tools, I would be very willing to use them, especially if they could provide personalised recommendations based on my learning progress.*"

9.4.3 Optimising Health Information Dissemination Mechanisms on Social Media Platforms

The results in Chapter 7 emphasise the influence of information channel on perceived usefulness, as well as the mediating role of perceived usefulness in the health information adoption process. The quantitative analysis shows that the information channel has a complete mediating effect on health information adoption through perceived usefulness (β = 0.107, p = 0.003, 95% CI: 0.040~0.183). Therefore, optimising the health information dissemination mechanisms on social media platforms is of great importance for improving the perceived usefulness and adoption rate of information. Based on this finding, the study proposes the following recommendations:

Improving the Recommendation Algorithms

It is recommended that social media platforms optimise their information recommendation algorithms. When recommending health-related information, they should consider not only user interests and interaction history but also information quality and source reliability. As News Editor C suggested, "*The algorithm should pay more attention to the reliability and professionalism of information, rather than just focusing on click-through rates and engagement.*"

An expert scoring system can be introduced to incorporate professional evaluations into the algorithm. Meanwhile, the algorithm should aim to avoid the filter bubble effect and moderately recommend information with different perspectives to promote a comprehensive understanding among users. As Researcher E pointed out, "*We need a balanced algorithm that can both recommend health information that users are interested in and ensure the diversity and reliability of the information.*"

Establishing a Rapid Review Mechanism for Health Information

For public health emergencies or popular health topics, platforms should establish a rapid review mechanism. A dedicated team comprising medical experts, communication scholars, and platform technicians can be assembled to conduct a timely review and processing of relevant information. As Doctor A emphasised, "*In public health events, the timeliness and accuracy of information are equally important, and we need a mechanism that can respond quickly.*"

A dual-check mechanism combining human and intelligent review should be implemented for highly sensitive or potentially high-impact health information. As Professor F suggested, "*A graded review system can be established, applying different review processes for health information of varying importance.*"

Developing Health Information Visualisation Tools

Encourage platforms to develop health information visualisation tools, transforming complex health data or medical concepts into easily understandable charts, animations, or interactive content. This cannot only improve the readability of information but also enhance user engagement, thereby increasing the perceived usefulness of the information. As Fitness Coach K stated, "*If we can convert some complex health data into intuitive charts or animations, more people will be willing to learn and understand this information.*"

Collaboration with professional medical institutions can be considered to ensure the accuracy and authority of the visualised content. As Nurse B suggested, "*Medical institutions can provide professional knowledge, while technology companies can be* *responsible for transforming this knowledge into attractive visualised content, and this cooperation can produce good results.*"

Implementing a Differentiated Information Display Strategy

Implement a differentiated information display strategy based on users' level of knowledge and cognitive involvement. Different depth versions can be provided for health information with higher professional complexity, allowing users to choose according to their own needs. As University Student H stated, "*Sometimes we need more in-depth health information, but sometimes a simple overview is enough, so it would be great if there were different depth versions to choose from.*"

Additionally, provide explanatory text or links for complex information to help users further understand the relevant background knowledge. As Housewife L suggested, "*For some professional terms or complex concepts if there could be simple explanations or links to more detailed explanations, it would be easier for us non-professionals to understand.*"

Establishing a User Feedback and Correction Mechanism

Set up convenient user feedback channels to encourage users to report suspicious health information. Establish a rapid response mechanism to verify and address user feedback in a timely manner. As Civil Servant I pointed out, "*We need a simple and direct way to report suspicious health information, and the platform should take user feedback seriously and take action quickly.*"

For information confirmed to be erroneous, in addition to deletion or labelling, a correction statement should be publicly released, and the correction information should be ensured to reach the original audience through algorithm adjustments. As Social Media Influencer D emphasised, "*When we find that we have disseminated incorrect information, I have a responsibility to correct it in a timely manner and ensure that the corrected information reaches all those who have seen the original information.*"

Platform optimisation strategies must account for varying technological familiarity and interface preferences across demographic groups. While the research findings primarily reflect younger, educated users' experiences, implementation should consider the distinct needs of older and less technology-proficient users. Interface design, algorithm transparency, and information visualisation should incorporate principles of inclusive design to ensure accessibility across different age groups and educational backgrounds. Platforms might consider developing specialised interfaces or settings for users with different technological proficiency levels, ensuring health information is effectively delivered to all population segments regardless of digital literacy.

9.4.4 Refining Policies and Regulations and Strengthening Multi-stakeholder Collaboration

The findings in Chapter 5 indicate that an effective response to the spread of health-related misinformation on social media requires multi-stakeholder collaboration. The interview results in the qualitative research stage show that multiple interviewees emphasised the importance of policies, regulations, and multi-stakeholder collaboration. Based on these insights, the study proposes the following recommendations:

Improving the Legal and Regulatory System

It is recommended that relevant authorities accelerate the formulation and improvement of laws and regulations regarding the dissemination of health information on social media. Clearly define the scope of health misinformation and stipulate the responsibilities and obligations of social media platforms, information publishers, and disseminators. As Professor F pointed out, "*We need a clear legal framework to regulate the dissemination of health information on social media, which not only can constrain undesirable behaviour but also provide guarantees for positive dissemination.*"

At the same time, supporting enforcement rules and penalties should be developed to enhance the operability of the regulations. As a Civil Servant I suggested, "*The* *regulations should clearly stipulate the punishment measures for intentionally disseminating health misinformation while also providing educational and corrective opportunities for unintentional but erroneous information dissemination.*"

Establishing a Multi-stakeholder Collaboration Governance Mechanism

Build a collaborative platform involving government departments, social media platforms, medical institutions, research institutions, and public representatives. Hold regular meetings to discuss health information governance strategies and coordinate actions among different parties. As News Editor C emphasised, "*Only through the collaboration of all parties can we effectively address the problem of the spread of health misinformation.*"

Establish an information-sharing mechanism to facilitate the timely exchange of the latest developments and best practices among different parties. As Researcher E suggested, "*We can establish a shared database to collect the monitoring and research results of various parties on health misinformation, providing data support for formulating governance strategies.*"

The collaborative platform should explicitly include representatives from diverse demographic groups, particularly those underrepresented in this study. Involvement of older adults and those with varying educational backgrounds would ensure governance mechanisms address the needs and perspectives of the broader population rather than primarily younger, educated social media users. This inclusive approach would help identify potential blind spots in health information governance strategies that might otherwise emerge when implementing interventions across diverse population segments.

Implementing Platform Social Responsibility Assessments

Establish a social responsibility assessment system for social media platforms' health information governance. Regularly evaluate the platforms' performance in health information management and misinformation prevention and make the evaluation results public. As Social Media Influencer D stated, “*Such assessments can encourage platforms to attach more importance to the management of health information and also help users choose more responsible platforms.*”

The assessment results can be linked to the platforms’ market access, tax incentives, and other policies to incentivise platforms to actively fulfil their social responsibilities. As Salesman G pointed out, “*If the platform’s social responsibility performance can be linked to its commercial interests, it will greatly increase the platform’s enthusiasm for managing health information.*”

Promoting International Cooperation and Experience Sharing

Given the cross-border dissemination characteristics of health misinformation, active international cooperation should be promoted. Participate in the formulation of international standards and norms and exchange governance experiences with other countries and regions. As Doctor A emphasised, “*Health issues are global, and we need international cooperation to address the challenge of the cross-border spread of health misinformation.*”

Establish a cross-national health information verification mechanism to jointly address the global challenge of health misinformation dissemination. As Professor F suggested, “*An international health information verification platform can be established, pooling the expertise of specialists from different countries to provide authoritative health information verification services for global users.*”

Supporting Relevant Research and Technological Innovation

Establish dedicated funds to support academic research and technological innovation in the field of health information dissemination on social media. Encourage interdisciplinary collaboration and promote the application of new technologies such as artificial intelligence and big data analysis in health information governance. As

Researcher E pointed out, "*We need more research to deepen our understanding of the patterns of health information dissemination in the social media environment, and we also need to actively explore the application of new technologies in this field.*"

Regularly organise academic forums and technical exchange meetings to facilitate the integration of theoretical research and practical applications. As Nurse B suggested, "*We can organise exchange meetings for healthcare professionals, technical experts, and social media practitioners, allowing professionals from different fields to discuss how to improve the health information environment on social media.*"

These multi-dimensional and multi-level governance strategies aim to comprehensively improve the quality of health information on social media, enhance users' identification abilities, optimise the dissemination mechanisms of platforms, and establish a multi-stakeholder collaboration governance system. Through the implementation of these strategies, not only can the spread of health misinformation be curbed, but accurate and useful health information can also better benefit the general public, ultimately improving public health literacy and overall health levels.

Overall, the formulation and implementation of these governance strategies require long-term efforts and close collaboration among all parties. As University Student H stated, "*Change will not happen overnight, but as long as we continue to work hard, I believe the health information environment on social media will certainly get better and better.*" This optimistic yet pragmatic attitude may be the key driving force behind the continuous improvement of the health information ecosystem on social media.

9.5 Directions for Future Study

Although this study has achieved certain results in the mechanisms of health-related misinformation dissemination and governance strategies on social media, there are still some limitations. These limitations point out directions for future research, and the following aspects are worth further exploration:

Cross-cultural Comparative Research

This study was mainly conducted in the Chinese cultural context, using theoretical frameworks and measurement tools derived from Western literature. Considering that cultural differences may affect the way health information is processed and adopted, future research should conduct cross-cultural comparative studies. This can not only verify the universality of this study's model but also reveal the role of cultural factors (such as collectivism vs. individualism, attitudes towards authority, etc.) in health information dissemination. It is suggested to select representative different cultural groups and adopt a multi-country, multi-language research design to explore the impact of cultural dimensions on health information dissemination mechanisms.

Research on Information Processing Patterns in Social Media Environments

Considering the problem of information overload in social media environments, users may rely more on intuitive judgments or the collective wisdom of social networks rather than carefully evaluating each piece of information. Future research can delve deeper into this social media-specific information processing pattern, including how to make health decisions in an environment where information flows rapidly and how social networks influence individual information adoption behaviours.

Longitudinal Tracking Research

This study uses cross-sectional data, which cannot capture the long-term effects and actual behavioural changes of health information adoption. Considering that health behaviour change is usually a long-term process, future research can design longitudinal tracking studies to observe users' health information reception, processing, and adoption behaviours over a period of time. This research design can reveal the cumulative effects of health information influence and the trajectory of changes in user attitudes and behaviours. It is recommended that mixed research methods be adopted, combining periodic questionnaire surveys, in-depth interviews, and social media data mining to comprehensively grasp the long-term effects of health information dissemination.

Research on Health Information Types and Contextual Factors

This study did not fully distinguish between different types of health information (such as preventive information, treatment information, chronic disease management information, etc.) and different health contexts (such as emergency public health events vs. daily health management). Future research can delve deeper into the adoption mechanisms and influencing factors under different types of health information and contexts. This may involve designing research targeting specific health topics or contexts to provide more refined theoretical insights and practical guidance.

Social Media Platform Characteristics Research

Different social media platforms (such as WeChat, Douyin, and Weibo) have differences in functional design, user groups, and information dissemination mechanisms. Future research can delve deeper into the impact of platform characteristics on health information dissemination. In particular, the short video format of emerging platforms like Douyin may bring entirely new patterns of health information dissemination and adoption. It is suggested that a multi-platform comparative research design be adopted to analyse how platform algorithms, user interfaces, social network structures, and other factors affect the speed, scope, and effectiveness of health information dissemination. This will provide targeted guidance for optimising health information governance strategies on different platforms.

Research on Individual Differences and Psychological Factors

Although this study considered the level of knowledge and cognitive involvement, there may be other important individual differences and psychological factors not included in the model. Future research can explore the impact of factors such as health beliefs, risk perception, emotional states, etc., on health information processing and adoption. This may involve interdisciplinary collaboration, combining theories and methods from fields such as psychology and behavioural economics to construct a more comprehensive model of health information adoption.

By specifically addressing these research limitations and exploring new research directions, future studies will be able to understand more comprehensively and deeply the mechanisms of health-related misinformation dissemination in social media environments and propose more effective governance strategies. This will not only help address the constantly evolving social media environment and emerging health challenges but also make important contributions to building a healthier and more reliable social media health information ecosystem.

9.6 Concluding Remarks

This study, centred on 'A Study of Dissemination Mechanisms and Governance Management of Health-related Misinformation on Social Media in China', provides new perspectives for addressing health information challenges in the digital age. Through systematic empirical investigation using mixed methods, the study has constructed a comprehensive model of health information adoption on social media whilst revealing the complex mechanisms of information dissemination and adoption.

Whilst the study has certain limitations, particularly regarding its cultural specificity and cross-sectional nature, its findings enrich the theoretical framework in the field of digital health communication whilst offering valuable insights for stakeholders. The theoretical model developed here extends existing frameworks by incorporating social media-specific factors and user characteristics, demonstrating how perceived usefulness mediates the relationship between information characteristics and adoption behaviour, with user knowledge and cognitive involvement playing significant moderating roles.

The practical recommendations proposed in this study, grounded in empirical evidence and theoretical understanding, offer actionable strategies for various stakeholders in the health information ecosystem. These strategies, ranging from enhancing information quality and credibility to strengthening multi-stakeholder collaboration, provide a comprehensive approach to addressing the challenges of health misinformation on social media platforms.

Looking forward, whilst tackling health-related misinformation on social media remains a long-term and arduous challenge, this study provides a foundation for future research and practical interventions. Through interdisciplinary collaboration and multi-stakeholder synergy, joint efforts to mitigating the negative impact of misinformation and promote the effective dissemination of accurate health information will undoubtedly make significant contributions to improving public health and social well-being.

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Appendix I: Interview Guide and Ethical Documentation

Interview Guide

Phase 1: Basic Perceptions of Health Information

1. Do you pay attention to health information? If so, is it on a regular basis or only when needed?
2. What types of health information are you most interested in? (e.g., diet, fitness, disease prevention)
3. What is your main purpose for seeking health information?
4. Have you ever obtained health information through social media? Was it helpful?
5. Which social media platforms do you mainly use to access health information?
6. Under what circumstances do you actively seek health information?
7. When you actively seek health information, what do you hope to gain? (e.g., knowledge, advice, specific action plans)
8. When you receive health information from official sources or friends on social media, do you choose to ignore or read it? Why?
9. How would you rate your level of health knowledge? Does this affect your attitude towards health information on social media?

Phase 2: Discrimination of Health Information

10. Do you believe you have the ability to discern the accuracy of health information posted on social media?
11. What factors do you think influence your judgment? (e.g., information source, content, credibility of the poster)
12. (Show Vignettes) Do you think the content in these videos is accurate? How did you make this judgment?
13. How do you determine if a piece of health information is accurate? Do you verify it with other sources?
14. When judging the credibility of health information, which characteristics of the information source do you value most? (e.g., professional background, public reputation)
15. Do you think different social media platforms differ in how they spread health information? How do these differences affect your trust and adoption of the information?
16. When you encounter health information that contradicts what you already know, what do you do? Do you understand the reasons behind this contradiction?

Phase 3: Behavioural Tendencies Towards Health Information

17. Are you willing to accept and adopt health information from social media? Why or why not?
18. Have you had experiences where you benefited from health information on social media? How did these experiences affect your attitude towards health information on social media?
19. When you receive health information on social media platforms, do you take action based on the recommendations? Why or why not?
20. Have you ever wanted to act on recommendations from social media health information but were unable to do so for various reasons? How did these experiences affect your attitude towards health information on social media?
21. How do you view and use health information on social media in emergency health situations? How does this differ from normal circumstances?
22. Do you comment on or share health information on social media? Why or why not?
23. How do other users' comments and feedback influence your views on health information and your decision to adopt it?
24. Who do you think should be responsible for ensuring social media users access accurate health information? (e.g., government, social media platforms, medical institutions)
25. What measures do you think can be taken to help users better identify and use health information on social media?
26. As a user, what responsibility do you think you should bear in dealing with health misinformation on social media?

Information Sheet
信息表

Study title: A Study of Dissemination Mechanisms and Governance Management of Health-related Misinformation on Social Media in China
研究题目：中国社交媒体健康相关误导信息的传播机制与治理管理研究

Researcher: Yitong Liu
研究人员：Yitong Liu

Approval number: EC1119 PG2 Ethics Form Approved
批准号：EC1119 PG2 伦理表获得批准

Please read this information carefully before deciding to take part in this research. It is up to you to decide whether to take part. If you are happy to participate you will be asked to sign a consent form.
在决定参与本研究之前，请仔细阅读本信息。您可以自行决定是否参与。如果您愿意参加，你将被要求签署一份同意书。

What is the research about?
这项研究是关于什么的？

This is a study conducted by a doctoral student at the University of Wales Trinity Saint David. The aim is to explore users' perceptions, discriminations and behavioural tendencies towards health information on social media, and to explore potential governance strategies to manage health misinformation.
这是威尔士三一圣大卫大学的一名博士生开展的一项研究。目的是探讨用户对社交媒体上健康信息的看法、辨别和行为倾向，并探索管理健康误导信息的潜在治理策略。

Why have I been asked to participate?
为什么请我参加？

You have been chosen to participate because you are an adult with experience in social media use.
你被选中参与，是因为你是一个有社交媒体使用经验的成年人。

What will happen to me if I take part?
如果我参加了，会发生什么事？

If you agree to participate, you will be invited to an in-depth semi-structured interview lasting approximately 45-90 minutes. The interview will be conducted [face-to-face/video call/voice call] at a time that is convenient for you. With your permission, the interview will be recorded to ensure accurate transcription. No follow-up interview will be required although the researcher will share the transcript with you, and you will have the opportunity to correct any content or add comments should you wish to.
如果您同意参与，您将被邀请进行一次约 45-90 分钟的半结构化深度访谈。访谈将[面对面/视频通话/语音通话]进行，时间将根据您的方便安排。在您允许的情况下，访谈将被录音以确保准确的转录。在征得您的同意后，将对访谈进行录音以确保记录准确无误。虽然研究人员会与您分享转录物，但无需进行后续访谈，您也有机会修改任何内容或添加评论，如果您愿意的话。

Are there any benefits to my taking part?
我参与其中有什么好处吗？

Whilst you may not benefit directly, your participation will contribute to a wider understanding of the dissemination of health information on social media, potentially improving strategies for managing health misinformation.
虽然您可能不会直接受益，但您的参与将有助于更广泛地理解社交媒体上健康信息的传播，潜在地改善管理健康错误信息的策略。

Are there any risks involved?
其中是否有任何风险？

This study is not expected to pose any risks. However, if you feel uncomfortable with any of the questions, you may choose not to answer or withdraw from the study at any time without penalty.
本研究预计不会带来任何风险。然而，如果您对任何问题感到不适，您可以选择不回答或随时退出研究，且不会受到任何惩罚。

Will my participation be confidential?
我的参与会被保密吗？

Yes. All information collected for this study will be kept strictly confidential. In compliance with the UK GDPR (General Data Protection Regulation), the DPA (Data Protection Act) 2018, the China Personal Information Protection Act 2021, the China Data Security Law 2021 and University policy, Your responses will be anonymised and any identifying information will be removed from the transcription. The researcher will not tell anyone you have taken part in this study. The researcher may repeat what you have said in a publication, but you will not be named.
是的。本研究收集的所有信息将严格保密。根据英国《一般数据保护条例》（GDPR）、2018 年《数据保护法》（DPA）、2021 年《中国个人信息保护法》、2021 年《中国数据安全法》和大学政策，您的回答将被匿名化，任何可识别身份的信息都将从记录中删除。研究人员不会告诉任何人您参与了本研究。研究人员可能会在出版物中重复您的发言，但不会透露您的姓名。

The data will be collected by the researcher. Your confidentiality will be safeguarded during the study by ensuring that the researcher will only see all the written and audio files and will not be linked to you personally.
数据将由研究人员收集。在研究过程中，你的保密性将得到保障，确保所有的书面和音频文件只有研究人员才能看到，不会与你个人联系起来。

Any personal data (i.e. names of participants) will be stored securely on a password-protected server researcher's computer. All data will be coded and anonymised to ensure it cannot be linked to you. The researcher will be the custodian of the data and will have sole access to view identifiable data.
任何个人数据（即带有参与者姓名的数据）都将安全地储存在研究者的电脑上，并有密码保护。所有的数据都将被编码和匿名化，以确保它不能与你联系起来。研究人员将是数据的保管人，并可单独访问查看可识别的数据。

What should I do if I want to take part?
如果我想参加，我应该怎么做？

You can inform the researcher that you want to take part by sending a return email or phone call. The researcher will then talk through the study with you before the interview and answer any further questions you may have. If you choose to participate, the study will then ask you to provide written informed consent on a university consent form.
你可以通过发回电子邮件或打电话的方式通知研究人员你想参加。然后，研究人员会在访谈前与你讨论研究内容，并回答你可能有的任何进一步问题。如果你选择参与，研究将要求你在大学同意书上提供一份书面的知情同意书。

What happens if I change my mind?

如果我改变主意会怎样？

You can withdraw from the study at any time during the interview, and up to four weeks following the interview, without your legal rights being affected. Simply inform the researcher in person or by email/phone that you want to withdraw from the study. Once you withdraw from the study the interview data collected will be destroyed.
你可以在访谈中的任何时候以及在访谈后的四个星期内退出研究，而不会影响你的合法权利。 你只需亲自或通过电子邮件/电话通知研究人员，你想退出研究。一旦你退出研究，收集的访谈数据将被销毁。

What will happen to the results of the research?
研究的结果将如何处理？

The findings from the study will be used to produce academic outputs showcasing anonymised key findings from the study.
研究结果将用于制作学术成果，展示匿名的主要研究成果。

The anonymised data will be retained for the duration of 5 years (from the time the data is gathered) as per the University Policy regarding data retention, including the researcher's personal ID to validate the data in case of actuation of fraud or fabrication.
根据大学的数据保存政策，匿名数据将保存 5 年（从收集数据时算起），其中包括研究人员的个人身份信息，以便在出现欺诈或捏造行为时验证数据。

Where can I get more information?
我在哪里可以获得更多信息？

Contact details for the Postgraduate Research Office or Director of Studies

Postgraduate Research Office pgresearch@uwtsd.ac.uk	Director of Studies Dr Steven Keen s.keen@uwtsd.ac.uk

What happens if something goes wrong?
如果出了问题，会发生什么？

In the unlikely case of concern or complaint, you should contact the Research Integrity and Governance Officer at pgresearch@uwtsd.ac.uk
如有疑虑或投诉，请发送电子邮件至 pgresearch@uwtsd.ac.uk 联系研究诚信与治理官员。

The University has insurance in place to cover its legal liabilities regarding this study.
大学已为这项研究的法律责任购买了保险。

Thank you for taking the time to read the information sheet and considering participating in the research.
感谢您抽出时间阅读信息表并考虑参与研究。

Consent Form
同意书

Study title: A Study of Dissemination Mechanisms and Governance Management of Health-related Misinformation on Social Media in China
研究题目：中国社交媒体健康相关误导信息的传播机制与治理管理研究

Researcher: Yitong Liu
研究人员：Yitong Liu

Approval number: EC1119 PG2 Ethics Form Approved
批准号：EC1119 PG2 伦理表获得批准

Please initial or tick the box(es) if you agree with the statement(s):
如果您同意这些声明，请在方框内签首字母或打勾。

I have read and understood the Information Sheet (*Version 1.1 of Information Sheet*) and have had the opportunity to ask questions about the study. 我已经阅读并理解了信息表（信息表 1.1 版），并有机会询问有关该研究的问题。	
I agree to take part in this study and agree for my data to be used for the purpose of this study. 我同意参加这项研究，并同意将我的数据用于这项研究的目的。	
I understand my participation is voluntary and I may withdraw during the interview and following the interview for any reason without my rights being affected (in which case the data will be destroyed). 我明白我的参与是自愿的，我可以在访谈期间和访谈后以任何理由退出，而我的权利不受影响（在这种情况下，数据将被销毁）。	
I understand that my interview will be recorded and transcribed verbatim. 我明白我的采访将被逐字记录下来。	
I understand my responses will be anonymised in reports of the research. 我明白我的回答在研究报告中会被匿名。	

Name of participant (print name)..
参加者姓名（打印姓名）
Signature of participant..
参加者签名
Date..
日期

Name of researcher (print name)..
研究者姓名（打印姓名）
Signature of researcher..
研究者签名
Date..
日期

Appendix II: Pre-survey Tables

Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	15.027	35.780	35.780	15.027	35.780	35.780	9.264	22.057	22.057
2	5.216	12.418	48.198	5.216	12.418	48.198	6.245	14.869	36.926
3	4.176	9.943	58.141	4.176	9.943	58.141	4.816	11.466	48.392
4	2.868	6.829	64.970	2.868	6.829	64.970	3.789	9.023	57.415
5	2.354	5.604	70.574	2.354	5.604	70.574	3.746	8.919	66.334
6	1.650	3.928	74.502	1.650	3.928	74.502	3.371	8.025	74.359
7	1.098	2.614	77.116	1.098	2.614	77.116	1.158	2.757	77.116
8	.881	2.099	79.215						
9	.667	1.589	80.803						
10	.636	1.514	82.317						
11	.583	1.388	83.705						
12	.539	1.283	84.988						
13	.513	1.222	86.210						
14	.471	1.120	87.330						
15	.447	1.065	88.395						
16	.421	1.003	89.398						
17	.368	.875	90.273						
18	.351	.835	91.108						
19	.334	.796	91.904						
20	.330	.786	92.690						
21	.280	.667	93.356						
22	.261	.620	93.977						
23	.246	.586	94.562						
24	.219	.522	95.084						
25	.199	.474	95.558						
26	.193	.459	96.017						
27	.169	.402	96.419						
28	.167	.398	96.818						
29	.148	.353	97.170						
30	.139	.331	97.501						
31	.137	.327	97.828						
32	.132	.314	98.142						
33	.117	.277	98.419						
34	.109	.260	98.679						
35	.102	.243	98.923						
36	.092	.219	99.142						
37	.083	.197	99.339						
38	.074	.176	99.514						
39	.062	.149	99.663						
40	.058	.138	99.801						
41	.046	.110	99.912						
42	.037	.088	100.000						

Extraction Method: Principal Component Analysis.

Table A: Total Variance Explained

Rotated Component Matrix[a]

	Component						
	1	2	3	4	5	6	7
IQ1	.753						
IQ2	.754						
IQ3	.702						
IQ4	.736						
IQ5	.760						
IQ6	.794						
IQ7	.831						
IQ8	.804						
IQ9	.760						
IQ10	.661						
IQ11	.782						
IQ12	.748						
IQ13	.686						
IQ14	.736						
IQ15	.753						
IS1					.833		
IS2					.849		
IS3					.850		
IS4					.748		
IS5					.738		
IC1		.830					
IC2		.821					
IC3		.797					
IC4		.851					
IC5		.829					
IC6		.814					
IC7		.792					
IC8		.721					
PU1			.865				
PU2			.886				
PU3			.880				
PU4			.887				
HIA1						.814	
HIA2						.804	
HIA3						.796	
HIA4						.859	
LK1				.675			
LK2				.738			
LK3				.734			
CI1				.806			
CI2				.729			
CI3				.744			

Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization.

a. Rotation converged in 8 iterations.

Table B: Rotated Component Matrix

Appendix III: Online Questionnaire

Social Media Health Information Perception Survey

社交媒体健康信息感知调查

No.***

Please read the following information carefully before deciding to take part in this research.

在决定参与本研究之前，请仔细阅读以下信息。

Dear Sir/Madam:

亲爱的朋友：

Greetings! Thank you very much for taking the time to read and complete this questionnaire.

您好！非常感谢您抽出宝贵的时间阅读并填写此问卷。

This is a study conducted by a doctoral student at the University of Wales Trinity Saint David to explore users' perceptions of health-related information on social media. The questionnaire consists of two parts, the first part is basic information about you and the second part is your general perception of health information on social media. Please read each question carefully and answer according to your actual situation and perception.

这是由威尔士三一圣大卫大学博士生开展的一项研究，旨在探讨用户对社交媒体上健康相关信息的感知。问卷由两部分构成，第一部分是您的基本信息，第二部分是您对社交媒体上健康信息的总体看法。请仔细阅读每个问题，并根据您的实际情况和看法进行回答。

This is a non-commercial survey, and your participation is completely anonymous and private. The information you provide is strictly confidential and the results are for academic purposes only. Your participation will be extremely helpful in studying social media health information. Thank you again for your participation!

这是一项非商业性调查，您的参与是完全匿名且不涉及个人隐私。您所提供的信息绝对保密，调查结果仅供学术研究。您的参与将对研究社交媒体健康信息有极大的帮助。再次感谢您的参与！

Yitong Liu
University of Wales Trinity Saint David
Email: 2105885@student.uwtsd.ac.uk

Note: If you have never read/obtained/followed health information through social media, please stop answering, thank you for your cooperation!

说明：如果您从未通过社交媒体阅读/获取/关注过健康信息，请您终止回答，谢谢合作！

Part 1 Demographics

第一部分：人口统计

Q1: Gender 性别

Male 男 ....O

Female 女..............................O

Q2: Age 年龄

Between 18 and 25 years ....O

18-25 岁 ....O

Between 26 and 35 years ....O

26-35 岁 ....O

Between 36 and 45 years ....O

36-45 岁 ....O

Between 46 and 55 years ....O

46-55 岁 ....O

Above 56 years ....O

56 岁以上...............................O

Q3: Qualifications 学历

Doctor degree........................O

博士研究生..........................O

Master degree........................O

硕士研究生..........................O

Bachelor degree ....O

本科学位...............................O

Diploma certificate.................O

专科文凭...............................O

High school certificate ....O

高中文凭...............................O

No certificate.........................O

无学历...................................O

Q4: Do you have background knowledge in medicine (including current/former medical-related occupations or current/former medical specialisation)?

您是否具有医学背景知识（包括当前/以前的医学相关职业或当前/以前的医学专业）？

Yes 是 ....O

No 否.....................................O

Q5: Do you regularly read/access/follow health information via social media?

您是否经常通过社交媒体阅读/访问/关注健康信息？

Yes 是 ....O

No 否 ....O

Part 2 Health Information on Social Media Perception

第二部分：社交媒体上健康信息的感知

Please select the level you think is appropriate for the following descriptions based on your previous experience of adopting health information on social media. The scale to be used in this part is described below:

这一部分是调查您对社交媒体健康信息的总体感知，请根据您之前在社交媒体上看到的健康信息的经验，选择您认为适合以下描述的级别。本部分中使用的比例如下所述：

1 .... Strongly Disagree

1 .... 强烈不同意

2... Disagree

2... 不同意

3... Slightly Disagree

3... 略微不同意

4... Neutral

4... 中立

5... Slightly Agree

5... 略微同意

6... Agree

6... 同意

7... Strongly Agree

7... 强烈同意

Q6: About Information Quality 关于信息质量		1	2	3	4	5	6	7
IQ1	This health information is coherent and logical in its content. 这条健康信息内容前后连贯，逻辑合理。	O	O	O	O	O	O	O
IQ2	The descriptions in this health information are accurate. 这条健康信息描述准确无误。	O	O	O	O	O	O	O
IQ3	This health information is comprehensive and complete in its content. 这条健康信息内容完整全面。	O	O	O	O	O	O	O
IQ4	The amount of information provided is appropriate, neither excessive nor lacking. 这条健康信息信息量合适，不冗余也不过少。	O	O	O	O	O	O	O
IQ5	The source of this health information is verifiable. 这条健康信息来源可查证。	O	O	O	O	O	O	O
IQ6	This health information is objective and impartial. 这条健康信息客观中立。	O	O	O	O	O	O	O
IQ7	The content of this health information is trustworthy. 这条健康信息内容值得信赖。	O	O	O	O	O	O	O
IQ8	This health information is relevant to my needs. 这条健康信息与我的需求相关。	O	O	O	O	O	O	O
IQ9	This health information is useful to me. 这条健康信息对我有用。	O	O	O	O	O	O	O
IQ10	This health information provides feasible suggestions. 这条健康信息给出了可行建议。	O	O	O	O	O	O	O
IQ11	This health information is novel and timely in its content. 这条健康信息内容新颖及时。	O	O	O	O	O	O	O
IQ12	The language used in this health information is straightforward and easy to understand. 这条健康信息语言通俗易懂。	O	O	O	O	O	O	O
IQ13	The presentation of this health information is user-friendly and readable. 这条健康信息呈现方式友好，便于阅读。	O	O	O	O	O	O	O
IQ14	The content of this health information is interesting and engaging. 这条健康信息内容有趣且引人入胜。	O	O	O	O	O	O	O
IQ15	The presentation format of this health information is appealing. 这条健康信息呈现形式吸引人。	O	O	O	O	O	O	O

Q7: About Information Source 关于信息来源		1	2	3	4	5	6	7
IS1	The disseminator of this information is an expert in the medical and health field. 这条健康信息的信息发布者是医疗健康领域的专家。	O	O	O	O	O	O	O
IS2	The disseminator of this information holds an authoritative position in the health domain. 这条健康信息的信息发布者在健康领域有权威地位。	O	O	O	O	O	O	O
IS3	The disseminator of this information is trustworthy.	O	O	O	O	O	O	O

Q7: About Information Source 关于信息来源		1	2	3	4	5	6	7
	这条健康信息的信息发布者值得信赖。							
IS4	The disseminator of this information comes across as approachable and amiable. 这条健康信息的信息发布者给人亲和友好的感觉。	O	O	O	O	O	O	O
IS5	The identity and background of the disseminator of this information are transparent. 这条健康信息的信息发布者的身份和背景信息透明。	O	O	O	O	O	O	O

Q8: About Information Channel 关于信息渠道		1	2	3	4	5	6	7
IC1	The interface design of this social media platform is professional. 这个社交媒体平台界面设计专业。	O	O	O	O	O	O	O
IC2	This platform is user-friendly and provides a good overall experience. 这个平台操作使用便捷，用户体验良好。	O	O	O	O	O	O	O
IC3	This platform supports user interaction and participation. 这个平台支持用户互动参与。	O	O	O	O	O	O	O
IC4	This platform is trustworthy and prioritises user privacy protection. 这个平台值得信赖，注重保护用户隐私。	O	O	O	O	O	O	O
IC5	The personalised recommendation algorithms and overall user experience of this platform are excellent. 平台的个性化推荐算法和整体用户体验很完善。	O	O	O	O	O	O	O
IC6	I frequently use this platform to obtain health information. 我经常使用这个平台获取健康信息。	O	O	O	O	O	O	O
IC7	The comments and interactions of other users on this platform also influence my adoption of health information. 平台上其他用户评论互动也会影响我的健康信息采纳。	O	O	O	O	O	O	O
IC8	This platform is commercially operated in moderation, without compromising its credibility. 平台适度商业化运营，没有降低其公信力。	O	O	O	O	O	O	O

Q9: About Perceived Usefulness 关于感知有用性		1	2	3	4	5	6	7
PU1	This health information provides me with expert knowledge about health conditions. 该健康信息为我提供了有关健康状况的专业知识。	O	O	O	O	O	O	O
PU2	This health information is helpful in answering my health-related questions. 该健康信息有助于回答我的健康相关问题。	O	O	O	O	O	O	O
PU3	This health information is helpful for improving my health condition. 该健康信息有助于改善我的健康状况。	O	O	O	O	O	O	O
PU4	This health information is valuable for my health-related decisions.	O	O	O	O	O	O	O

Q9: About Perceived Usefulness 关于感知有用性		1	2	3	4	5	6	7
	该健康信息对我做出与健康有关的决定很有价值。							

Q10: About Health Information Adoption 关于健康信息采用		1	2	3	4	5	6	7
HIA1	I will endorse this health information (e.g., like, upvote). 我将支持此健康信息（例如如，点赞、赞同）。	O	O	O	O	O	O	O
HIA2	I will share this health information with others (e.g., share, retweet). 我会与他人分享此健康信息（例如，分享、转发）。	O	O	O	O	O	O	O
HIA3	I will adjust my health behaviours based on this information. 我会根据这些信息调整自己的健康行为。	O	O	O	O	O	O	O
HIA4	I will follow this information's suggestions in my health management. 我会根据信息中的建议进行健康管理。	O	O	O	O	O	O	O

Q11: About Self-Knowledge Level Assessment 关于自我知识水平评估		1	2	3	4	5	6	7
LK1	I have good knowledge about this health topic. 我对这一健康主题有很好的了解。	O	O	O	O	O	O	O
LK2	I am familiar with this health information topic. 我熟悉这一健康信息主题。	O	O	O	O	O	O	O
LK3	I am expertise in this health topic. 我在这一健康主题上具有专业知识。	O	O	O	O	O	O	O

Q12: About Self-Cognitive Involvement Assessment 关于自我认知卷入度评估		1	2	3	4	5	6	7
CI1	I am deeply engaged with this health information. 我深入了解这一健康信息。	O	O	O	O	O	O	O
CI2	I put considerable mental effort into processing this health information. 我花了很大的精力来处理这一健康信息。	O	O	O	O	O	O	O
CI3	This health information captures my attention and stimulates my thinking. 该健康信息吸引了我的注意力并激发了我的思考。	O	O	O	O	O	O	O

—END OF QUESTIONNAIRE—

—THANK YOU—