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PREDICTIVE MODELING OF AUDIENCE SATISFACTION IN CHINESE WEB DRAMAS: A BIG DATA ANALYTICS APPROACH

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Abstrak

Walaupun drama web Cina berkembang pesat, beberapa produksi masih mengalami kepuasan penonton yang rendah. Masalah ini diperburuk oleh penggunaan data besar yang kurang optimum dalam meramalkan kepuasan penonton, meningkatkan ketidakpastian operasi dan risiko pasaran. Walaupun terdapat kajian terdahulu mengenai kepuasan penonton drama web Cina namun model ramalan berasaskan data masih belum dibangunkan. Kajian ini bertujuan membangunkan model ramalan inklusif bagi kepuasan penonton drama web Cina, merangkumi lima konstruk utama: motivasi menonton, kepuasan penonton, pendedahan kepada drama web, penglibatan penonton di media sosial, dan saiz komuniti media sosial. Model ini dibangunkan berasaskan teori Uses and Gratifications Theory (UGT) serta teori Channel Complementarity Theory (CCT), dengan sebelas hipotesis telah dicadangkan untuk kesahan. Pensampelan sistematik berstrata digunakan untuk memilih 288 drama web Cina berdasarkan 16,057,255 entri media sosial tidak berstruktur dan 3,744 rekod berstruktur yang diekstrak melalui analitis data besar. Analisis sentimen dijalankan untuk menukar komen tidak berstruktur kepada dataset berstruktur, dan semua hipotesis diuji menggunakan 6,048 rekod berstruktur akhir melalui SPSS 29.0 dan SmartPLS 4.1. Kajian ini mengesahkan enam hubungan langsung positif antara pemboleh ubah yang dikaji. Pendedahan drama web dan penglibatan media sosial menjadi perantara separa antara motivasi menonton dan kepuasan penonton, manakala saiz komuniti media sosial memoderasi secara positif hubungan antara motivasi menonton dengan kepuasan penonton, serta antara pendedahan drama web dengan penglibatan penonton di media sosial. Kajian ini menyumbang kepada pemahaman mengenai kepuasan penonton drama web dan faktor penentunya. Dari segi teori, kajian ini memperkayakan UGT dan CCT dengan mengesahkan dan memperluas penerapannya untuk membina model ramalan dalam konteks drama web Cina. Dari segi metodologi, kajian ini menggunakan pendekatan analitis data besar yang inovatif, termasuk integrasi analisis sentimen. Dari segi praktikal, kajian ini menyediakan panduan bermakna kepada pihak berkepentingan drama web dan agensi pengawalseliaan kerajaan.

Kata Kunci: Kepuasan penonton, Penglibatan penonton di media sosial, Saiz komuniti media sosial, Motivasi menonton, Pendedahan kepada drama web

Abstract

Chinese web dramas have grown rapidly as a media sector, but some shows still face low audience satisfaction. This challenge is compounded by the underutilization of big data for audience satisfaction, forecasting among Chinese web drama stakeholders, exacerbating operational uncertainties and market risks. Despite this, prior studies on Chinese web drama audience satisfaction have not developed data-driven, predictive models. This study aims to develop an inclusive predictive model of audience satisfaction in Chinese web dramas, incorporating five constructs: viewing motivation, audience satisfaction, web drama exposure, audience social media engagement, and social media community size. The model is grounded in Uses and Gratifications Theory (UGT) and Channel Complementarity Theory (CCT) and operationalized through big data analytics. Eleven hypotheses were proposed for validation. Stratified systematic sampling was employed to select 288 Chinese web dramas, from which 16,057,255 unstructured social media entries and 3,744 structured records were extracted via big data analytics. Sentiment analysis was applied to convert the unstructured comments into structured datasets, and all hypotheses were tested using 6,048 final structured records via SPSS 29.0 and SmartPLS 4.1. The study confirmed six positive direct relationships among the studied variables. Web drama exposure and social media engagement partially mediated the link between viewing motivation and satisfaction, while social media community size positively moderated the relationships between viewing motivation and satisfaction, and between web drama exposure and social media engagement. This study contributes to understanding web drama audience satisfaction and its antecedents. Theoretically, it enriches UGT and CCT by validating and extending their application to develop the predictive modelling in the context of Chinese web dramas. Methodologically, it employs a novel big data analytics approach integrating sentiment analysis. Practically, it provides actionable insights for web drama stakeholders and governmental regulatory agencies.

Keywords: Audience satisfaction, Audience social media engagement, Social media community size, Viewing motivation, Web drama exposure

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List of Abbreviations

AI	Artificial Intelligence
AS	Web Drama Audience Satisfaction
AVE	Average Variance Extracted
CCA	Confirmatory Composite Analysis
CCT	Channel Complementarity Theory
CFA	Confirmatory Factor Analysis
CI	Confidence Interval
CNN	Convolutional Neural Networks
CNNIC	China Internet Network Information Center
CNRTA	China's National Radio and TV Administration
CWD	a Certain Web Drama
EFA	Exploratory Factor Analysis
GoF	Goodness-of-fit Index
HTMT	Heterotrait-monotrait Ratio
IQR	Interquartile Range
LM	Linear Regression Model
MAE	Mean Absolute Error
NCEI	the Number of Comments Expressing Intent for a Certain Web Drama
NLP	Natural Language Processing
PLS-SEM	Partial Least Squares Structural Equation Modeling
RMSE	Root Mean Square Error
RNN	Recurrent Neural Networks
SMCS	Social Media Community Size
SEM	Structural Equation Modeling
SME	Web Drama Audience's Social Media Engagement
SVR	Support Vector Regression
SPSS	Statistical Package for Social Sciences

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UGT	Uses and Gratifications Theory
VIF	Variance Inflation Factor
VM	Web Drama Viewing Motivation
WDE	Web Drama Exposure

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CHAPTER ONE

INTRODUCTION

1.1 Introduction

This study focuses on predictive modeling of audience satisfaction in Chinese web dramas grounded in the theoretical frameworks of Uses and Gratifications Theory (UGT) and Channel Complementarity Theory (CCT) through a big data analytics approach. Based on big data analytics, the developed model enables Chinese web drama stakeholders (e.g., content producers, streaming platforms, advertisers) to proactively conduct data-driven predictive analysis of audience satisfaction, thereby facilitating evidence-based targeted interventions designed to elevate audience satisfaction. These capabilities are projected to optimize organizational decision-making, reduce operational uncertainties, and mitigate market risks for these stakeholders.

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This chapter serves as a foundational roadmap for the entire study. To begin with, this chapter introduces the background of the study. Subsequently, the problem statement is presented to clarify the research problem, research aim, and existing gaps. Moreover, four research questions are outlined, each accompanied by a corresponding research objective. In addition, the significance of the study is discussed, including knowledge significance, theoretical significance, methodological significance, and practical significance. Furthermore, this chapter

elaborates on the conceptualization of five constructs that play a crucial role in developing the predictive model. Following this, the research scope is defined. Next, the organization of the thesis is presented in alignment with the actual structure of the research. Finally, the chapter concludes with a summary.

1.2 Background of the Study

With the advancement of society, new media has surged at an unprecedented pace, deeply penetrating various aspects of social life. The new media era is also referred to as the digital age (Bove & Rhodes, 2025; Tsai & Chistyakova, 2022) or the second media age (Poster, 2018). In this era, numerous emerging phenomena have emerged on the Internet; web drama is one of them.

As a new form of audio-visual program, web drama refers to serialized dramatic content distributed primarily via the Internet (Hu, 2021; Mi et al., 2022). Built on Internet technology, web drama targets Internet users as its primary potential audience and seeks to satisfy their needs for entertainment, relaxation, escapism, passing time, information seeking, and social interaction through compelling and immersive narratives (Hu, 2021; Wang, 2022). Historically, web drama originated in the United States in the mid-1990s; the first recognized web drama is *The Spot* (1995–1997) (Monaghan, 2017).

Since 2018, Chinese web dramas have experienced rapid development. According to the statistics of Maoyan app (Chinese media industry's professional big data platform), a total of 2,194 Chinese web dramas have been broadcast since 2018, 495 more than Chinese TV dramas during the same period. In the first half of 2024, the playback volume of Chinese web dramas increased by 35.1% year-on-year (CNNIC, 2024). Many excellent Chinese web dramas, such as *The Longest Day In Chang'an*, *Joy of Life,* and *My Heroic Husband*, became popular on the Internet (Hu, 2021; Wang, 2022; Zhou & Zhi, 2020). Taking *The Longest Day In Chang'an* as an example*,* as of August 1, 2024, its playback volume had reached 3.37 billion on Chinese Tiktok, and its official Weibo account had amassed over 1.96 million followers. Additionally, this web drama received a Douban score of up to 8.1 and won 12 entertainment industry awards. These facts mirror the growing popularity of Chinese web dramas among audiences.

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In the meantime, audience satisfaction is receiving increasing attention in the media industry recently. Audience satisfaction refers to the post-consumption assessments of the media, its content and media-generated activity (Periaiya & Nandukrishna, 2023). It is one of the most important consequences of media experiences for audience (Kim & Kim, 2020a). With the development of online audio-visual programs, it is of great significance to be committed to investigating their audience satisfaction (Han et al., 2023a; Limic & Limb, 2023; Ng et al., 2022). Furthermore, to cope with increasingly fierce market competition, enterprises are expected to

continuously increase customer satisfaction in the digital age (Maulana, 2020; Makanyeza et al., 2021). Accordingly, the web drama stakeholders are required to constantly enhance audience satisfaction in order to better address the challenges of the media market.

Moreover, predictive modeling has received increasing interest in recent years (Adewusi et al., 2024; Ijomah et al., 2024; Shoetan et al., 2024). Predictive modeling involves building models to forecast the future results based on historical data (Adewusi et al., 2024). It could offer the powerful abilities of predicting future developments and drawing conclusions to the researchers and decision makers (Adewusi et al., 2024; Adenyi et al., 2024). For the media industry, predictive modeling can serve to address the challenges posed by the new media era and identify emerging developmental trends (Shao, 2024). Furthermore, advancements in predictive modeling are poised to catalyze innovation within the new media landscape. Therefore, it is considerably valuable to conduct the research on predictive modeling of audience satisfaction in Chinese web dramas.

Furthermore, the big data analytics approach has gained more emphasis in the media industry. In recent years, the type and scope of social research have been revolutionized by social media big data analytics (Hair et al., 2019b). Meanwhile, media industry is required to seek out more comprehensive data on audience, such as big data in the Internet era (McQuail & Deuze, 2020). Recently, Zhou and Zhao

(2021) apply the big data analytics approach to explore the media effect evaluation of audio-visual information through the lens of social media application. Zhou and Zhao (2021) encourage communication researchers to employ big data technology to examine audience motivations, emotions, and behaviors.

According to Babbie (2020) and Clark et al. (2022), social media big data analytics approach is extremely dynamic and promising in social research. As stated by Boyle and Schmierbach (2024), computer-aided techniques are becoming more common as a result of the large volumes of publicly available data which are known as big data coming from social media and other sources. Likewise, social media big data analytics approach frequently employs sentiment analysis in communication research to discover valuable information and obtain original ideas in the Internet era (Liu, 2020; Zhou & Zhao, 2021).

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Notably, the advancement of the Internet and innovations in computing capability have created abundant opportunities for the application of big data analytics. According to CNNIC (2024), as of June 2024, the number of Internet users in China reached nearly 1.1 billion. Thomala (2024) reports that China's social media penetration rate was 74.2% in 2023, with approximately 1.06 billion active users. Furthermore, China ranks second globally in computing capability (Xinhua News Agency, 2023). Therefore, this study employs the big data analytics approach to

conduct predictive modeling of audience satisfaction in Chinese web dramas. This is a timely and significant research topic.

1.3 Problem Statement

Recently, Chinese web dramas have experienced rapid development and have increasingly become an integral part of Internet users' daily lives (CNNIC, 2024). Numerous prominent Chinese web dramas have attracted a substantial audience and achieved high levels of audience satisfaction (Cao et al., 2023; Hu, 2021; Wang, 2022). These web dramas have not only provided entertainment and spiritual enrichment to audiences, but also generated economic returns for web drama stakeholders (Ji, 2023; Li, 2023). They have contributed to the prosperity of the media industry.

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However, a notable issue is that certain Chinese web dramas exhibit low audience satisfaction and have failed to gain favorable reception among viewers (Cao et al., 2023; Kong, 2020; Wang, 2022). According to data from the Douban website, a leading Chinese cultural review and social platform, in 2024, there were 112 Chinese web dramas that received a Douban score below 5 points on a 10-point scale or lacked an available score. These web dramas are generally considered to be low-satisfaction productions (Hu, 2020). Due to low audience satisfaction, the audiences are increasingly likely to disengage from these Chinese web dramas. As a

result, this issue could undermine audience retention and threaten the long-term sustainability of the web drama industry.

Crucially, this aforementioned challenge is compounded by the underutilization of big data among Chinese web drama stakeholders for audience satisfaction forecasting (Zhao, 2021; Zeng, 2024; Zhou & Zhao, 2021). Big data on Chinese web dramas are accessible online, including real-time statistical datasets derived from large-scale social media comments, social media metrics (e.g., volume of likes and shares), major search engines, and professional big data platforms (Zhou & Zhao, 2021). Big data, regarded as information assets (Xu et al., 2023; Yanlin & Haijun, 2020), could be unlocked and transformed into value, including predictive value, when leveraged effectively (Chaudhary et al., 2021; Demirbaga et al., 2024; Liu et al., 2022). However, the underutilization of big data in audience satisfaction forecasting impedes stakeholders from performing timely predictive analysis of audience satisfaction, thereby exacerbating operational uncertainties and heightening market risks. This issue thus warrants urgent attention.

For example, a substantial volume of user-generated comments emerges in response to Chinese web dramas on the social media platform Weibo. Statistical data reveal that the web dramas *The Pursuer*, *Dear Herbal Lord*, and *Insect Totem* have amassed 5,938, 4,327, and 1,264 comments, respectively, on Weibo as of August 15, 2024. However, to date, Chinese web drama stakeholders have yet to effectively leverage

such big data for audience satisfaction forecasting (Li, 2022; Li, 2024; Mi et al., 2022), which hampers their ability to proactively implement measures to improve audience satisfaction. Currently, the Douban scores of these web dramas are all below 5, indicating low audience satisfaction (Hu, 2020). This undoubtedly elevates the market risks associated with such underperforming web dramas.

The two aforementioned challenges collectively highlight an urgent need for targeted predictive modeling of audience satisfaction that can dynamically adapt to the evolving Chinese web drama market. However, existing scholarly research on Chinese web drama audience satisfaction has yet to establish tailored, data-driven predictive models that account for the distinctive features of the Chinese digital content ecosystem, thus depriving web drama stakeholders of a systematic tool to enhance organizational decision-making, reduce operational uncertainties, and mitigate market risks amid intensifying competition (Cao et al., 2023; Hu, 2021; Liu et al., 2022). Therefore, this study aims to develop a comprehensive predictive model of audience satisfaction in Chinese web dramas using a big data analytics approach. Grounded in big data analytics, this model equips Chinese web drama stakeholders with the capability to conduct proactive, data-driven predictive analysis of audience satisfaction, thereby facilitating evidence-based targeted interventions to enhance audience satisfaction. Specifically, building on the above analysis, this study identifies several interrelated research gaps: knowledge gaps, theoretical gaps,

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methodological gaps, and practical knowledge gaps, all of which are discussed below.

From a knowledge perspective, this section reveals several existing research gaps. First, research on the antecedents of audience satisfaction in Chinese web dramas remains limited (Cao et al., 2023; Genggong & Tawai, 2024; Huang et al., 2023). In recent years, there has been a growing and thoughtful focus on audience satisfaction among communication investigators (Ahmed & Abdulkareem, 2023; Genggong & Tawai, 2024; Limic & Limb, 2023). However, researchers remain uncertain about the antecedents of audience satisfaction in Chinese web dramas (Wang, 2022; Yang, 2023). This uncertainty may arise from the rapid, dynamic evolution of Chinese web dramas, which has outpaced academic inquiry, as well as from the barriers to in-depth, representative research posed by their large and geographically dispersed audience base (Camilleri & Falzon, 2020; Omar & Dequan, 2020).

Owing to the uncertainty regarding which antecedents of audience satisfaction should be targeted for action, the enhancement of audience satisfaction may have faced significant challenges. By addressing this research gap, the present study equips stakeholders in the Chinese web drama sector with evidence-based insights to implement targeted interventions on the underlying antecedents of audience satisfaction, thereby facilitating the enhancement of this key outcome variable. This strategic framework not only potentially reduces operational uncertainties and

mitigates market risks but also contributes to the sustainable development of the Chinese web drama ecosystem.

In addition, web drama exposure and audience social media engagement have received growing attention in recent years (Barry et al., 2024; Mi et al., 2022; Tsai & Lin, 2023). Web drama exposure is a form of audio-visual content consumption during which audiences actively seek out, encounter, and engage with specific web drama content (Mi et al., 2022). Meanwhile, audience social media engagement, such as interacting with others or posting comments, is commonly used as an extension of web drama exposure among audiences (Tsai & Lin, 2023).

Second, the mediating effects of web drama exposure and audience social media engagement on audience satisfaction in the Chinese web drama context have been underexplored empirically (Khatri et al., 2021; Mi et al., 2022; Tylka et al., 2023). Previous research has proposed the mediating effects of audio-visual media exposure and audience social media engagement on audience satisfaction. For instance, research indicated that audio-visual media exposure mediates the relationship between viewing motivation and viewing satisfaction in the context of TV programs (Kim & Kim, 2020a). Moreover, scholarly inquiry revealed that social media engagement plays a mediating role in the relationship between motivations and body satisfaction (Tylka et al., 2023).

Besides that, the sequential mediating effect of these two mediating variables warrants serious attention (Kim & Kim, 2020a). Studies have shown that millions of individuals utilize social media to share their audio-visual content viewing experiences with others (Khanom, 2023; Odunaiya et al., 2020). Chinese audiences actively shared their audio-visual content viewing experiences across time and space through interactive behaviors such as liking, commenting, and sharing on social media platforms (Dan & Erdenebold, 2024). Additionally, social TV research, which is considered a frontier, indicates that audiences engage in social media interactions following exposure to TV programs within specific content domains (Elareshi et al., 2022; Habes et al., 2022). Likewise, as a form of audio-visual content consumption, web drama exposure frequently occurs subsequent to audience social media engagement (Zhang & Liang, 2024). This phenomenon suggests that these two factors may serve as sequential mediators, thereby amplifying their influence on audience satisfaction.

Consequently, this study proposes to examine web drama exposure and audience social media engagement as mediating variables influencing audience satisfaction within the context of Chinese web dramas, thereby developing a comprehensive predictive model of audience satisfaction based on these relationships. Particularly, web drama exposure and audience social media engagement may serve as the sequential mediators, constituting a multiple-step multiple mediation mechanism

(Hayes, 2022). This mediation mechanism could extend the existing body of knowledge on audience satisfaction prediction.

Although existing studies have explored these two mediating variables, research on their mediating effects toward audience satisfaction in the context of Chinese web dramas remains limited (Khatri et al., 2021; Mi et al., 2022; Tylka et al., 2023), particularly regarding their sequential mediating effect (Hu, 2021; Ji, 2023; Tsai & Lin, 2023). To address the existing research gap, this study attempts to examine the mediating roles of these two factors.

Third, the moderating effect of social media community size in audience satisfaction research within the context of Chinese web dramas has been insufficiently studied empirically (Jiang et al., 2019; Nepomuceno et al., 2020). Academic attention has increasingly been directed toward social media community size in recent years due to its growing influence on media usage and effects (Nepomuceno et al., 2020). Social media community size denotes the total number of social media entities that engage in sustained interactions centered on a shared element of interest within a group in a social media network (Cho & Wash, 2021; Naranjo-Zolotov et al., 2021). To date, a few prior studies have employed social media community size as a moderating variable (Jiang et al., 2019; Nepomuceno et al., 2020). Nonetheless, empirical evidence remains inadequate regarding the moderating effect of social media

community size in audience satisfaction research within the context of Chinese web dramas (Jiang et al., 2019; Nepomuceno et al., 2020).

Specifically, previous studies not only lack sufficient research on the moderating effect of social media community size, but also have not reached a consensus on whether this moderating effect is positive or negative, indicating a need for further investigation (Nepomuceno et al., 2020; Zhang et al., 2022). Given these considerations, this study seeks to incorporate social media community size as a moderating variable in the relationships among key predictors and audience satisfaction, thereby developing a more accurate and comprehensive predictive model.

Theoretically, several theoretical gaps are identified by this study. First, UGT, widely regarded as a prominent and dynamic framework in communication research (McQuail & Deuze, 2020; West & Turner, 2020), has been rarely applied to the study of audience satisfaction in web dramas (Alhabash et al., 2024; Chapman & Abraham, 2024; Syafira & Dharmmesta, 2024). This results in a lack of theoretically grounded frameworks for scholars to explain web drama audiences' motivations, behaviors, and satisfaction (Chapman & Abraham, 2024; Hu, 2021; Syafira & Dharmmesta, 2024).

Meanwhile, research on web drama audience satisfaction is expected to become a prominent issue of interest to both the academic community and the media industry (Gong & Huang, 2022). The application of UGT in research on web drama audience satisfaction could contribute additional empirical evidence to UGT, thereby enriching its scope of study. More importantly, benefiting from emerging technologies or novel research methods, the application of UGT in web drama audience research may contribute to new theoretical breakthroughs in UGT (McQuail & Deuze, 2020; West & Turner, 2020).

Second, CCT, widely recognized for its insights into the complementarity between new and traditional media, has largely overlooked the cross-platform complementarity among different new media, such as the synergy between video platforms and social media (Jiang & Liu, 2022; Qin et al., 2023; Wang et al., 2024). This theoretical gap constrains CCT's explanatory power regarding contemporary new media usage patterns. To date, new media have become deeply embedded in daily life in China, exerting significant impacts on individuals' cognition, emotions, and behaviors (Chen et al., 2024; Geng et al., 2024; Yang & Wang, 2021). Empirical evidence further underscores this context: CNNIC (2024) reports that China had approximately 1.1 billion Internet users as of June 2024, while Chinese social media platforms recorded around 1.06 billion active users in 2023 (Thomala, 2024). These trends highlight an urgent need for CCT to account for the complementary roles of diverse new media platforms.

Third, a predictive model explaining the integration of these theories has remained understudied (Menon, 2022; Qin et al., 2023; Zadeh, 2022). In recent years, numerous communication studies have focused on prediction from the perspective of UGT (Menon, 2022; Thongmak, 2021; Zadeh, 2022). Meanwhile, a limited number of predictive studies in communication have been conducted through the lens of CCT in recent years (Neyazi et al., 2019; Qin et al., 2023). However, communication research on predictive models that explain the integration of UGT and CCT in audience satisfaction studies is scarce, which could contribute to refining these theories and enhancing their practical utility in prediction.

In this study, the integration of UGT and CCT in predictive modeling is theoretically compatible, feasible, and imperative. Above all, UGT and CCT share key commonalities that justify their theoretical integration. Both focus on media usage behavior (McQuail & Deuze, 2020; Qin et al., 2023; Wang et al., 2024), emphasize individuals' active role in selecting and engaging with media (Liao et al., 2021; McQuail & Deuze, 2020), and center on how media use fulfills personal needs (Dutta-Bergman, 2004b; McQuail & Deuze, 2020).

Additionally, UGT and CCT have a complementary relationship that supports their integration. UGT explains why individuals use media (West & Turner, 2020), while CCT focuses on how audiences engage with diverse media (Jiang & Liu, 2022; Qin

et al., 2023; Wang et al., 2024). Together, they enable a more comprehensive analysis of media use, making their integration theoretically justified. Furthermore, given that both theories center on audience needs, media usage behavior, and the fulfillment of those needs, integrating them allows for the effective inclusion of all study variables within the model and clarifies their relationships with other constructs. This integration thus yields a more comprehensive and theoretically grounded predictive framework.

Methodologically, the present study identifies several methodological gaps. First, there are few communication research methods capable of efficiently collecting credible and large-scale data in the Internet era without influencing the object of study (Abkenar et al., 2021; Babbie, 2020; Zhou & Zhao, 2021). Most communication research methods, including experiments, survey research, and qualitative field studies, inherently involve data collection processes that may influence the object of study. It may lead to *the Hawthorne effect*, which refers to the phenomenon whereby individuals' behavior changes when they become aware of being observed, due to the attention received from researchers (James & Vo, 2022). This is a significant concept that researchers should consider when designing studies and drawing conclusions (James & Vo, 2022).

Apart from *the Hawthorne effect*, data collected through experiments, survey research, or qualitative field studies may face credibility challenges, namely, that

inconsistent data may arise due to variations among respondents or researchers, which could negatively affect the study's conclusions. In contrast, content analysis, a widely adopted unobtrusive research method, allows for the collection of credible data without direct interaction with the object of study (Babbie, 2020; Boyle & Schmierbach, 2024; Croucher & Cronn-Mills, 2024). However, it is often inadequate and, to some extent, ill-suited for large-scale data collection.

Confronted with this research gap, Babbie (2020) introduces a big data analytics approach that enables the study of social behavior without interfering with natural interactions. This approach is widely regarded as an emerging and rapidly evolving research method (Babbie, 2020; Boyle & Schmierbach, 2024; Croucher & Cronn-Mills, 2024). Meanwhile, it is evident that big data pertaining to Chinese web dramas is present on the Internet in recent years and exhibits the characteristics of high volume, velocity, variety, and veracity (Castellani & Rajaram, 2021). The big data analytics approach can effectively transform big data into actionable insights that can be utilized by the web drama industry (Li, 2022; Li, 2024; Mi et al., 2022), thereby facilitating the full realization of big data's profound potential.

Second, due to limitations in sampling techniques, conclusions drawn from many new media audience studies employing quantitative research are often not generalizable to the target population (Abdul Hamid, 2022; Babbie, 2020; Jin et al., 2023). Owing to objective constraints, such as the inability of communication

researchers to obtain a complete list of web drama audiences, probability sampling cannot be employed to collect audience data (Babbie, 2020; Croucher & Cronn-Mills, 2024; Scharrer & Ramasubramanian, 2021). Given that, nonprobability sampling is frequently the only viable option available to researchers (Babbie, 2020). Nevertheless, nonprobability sampling does not guarantee that the resulting sample will be representative of the target population being studied (Babbie, 2020; Croucher & Cronn-Mills, 2024; Scharrer & Ramasubramanian, 2021). As a result, the conclusions reached cannot be generalized to the target population (Babbie, 2020; Croucher & Cronn-Mills, 2024; Jin et al., 2023). It indicates that these conclusions are frequently associated with risk.

Due to the methodological gaps outlined above, most existing communication research methods are ill-suited for modeling audience satisfaction in Chinese web dramas. In contrast, the big data analytics approach, which emerges as a novel research method, offers significant advantages (Babbie, 2020) and effectively addresses the limitations identified earlier. More importantly, it enables the unlocking of big data's predictive potential, allowing stakeholders to conduct predictive analysis proactively. Furthermore, this approach enhances the accuracy of the developed predictive model. Consequently, its adoption is essential for predictive modeling of audience satisfaction in Chinese web dramas.

Practically, this study identifies several gaps in practical knowledge. First, there is a paucity of empirical research that provides stakeholders with evidence-based guidance for proactively conducting data-driven predictive modeling of audience satisfaction in Chinese web dramas (Hu, 2021; Liu et al., 2022; Mi et al., 2022). In recent years, audience satisfaction in online audio-visual programs has attracted growing attention from web drama stakeholders (Han et al., 2023a; Limic & Limb, 2023; Ng et al., 2022), reflecting a growing recognition of its strategic importance. To effectively navigate competitive pressures in the media market, web drama stakeholders are required to continuously enhance audience satisfaction (Cao et al., 2023; Hu, 2021; Wang, 2022).

Concurrently, predictive modeling has received increasing scholarly attention in recent years (Adewusi et al., 2024; Ijomah et al., 2024; Shoetan et al., 2024). This analytical approach equips researchers and decision-makers with robust capabilities to forecast future trends and derive evidence-informed insights (Adewusi et al., 2024; Adenyi et al., 2024). Specifically in the media industry, predictive modeling serves to address disruptions brought by the new media era and proactively identify emerging developmental trajectories (Shao, 2024). Overall, it is imperative for stakeholders to conduct data-driven predictive modeling of audience satisfaction within the landscape of Chinese web dramas.

Nevertheless, despite the significance of this topic, prior studies have been limited in providing evidence-based guidance for web drama stakeholders to proactively conduct such analyses. Potential contributing factors include the vast and geographically dispersed audience base of web dramas as well as technical constraints associated with data-driven predictive modeling (Cao et al., 2023; Hu, 2021; Wang, 2022). This lack of actionable guidance may impede stakeholders' ability to conduct timely predictive analysis, which could in turn exacerbate operational uncertainties and increase market risks for these stakeholders. These observations highlight a notable gap in practical application.

Thus, it holds notable practical implications to conduct empirical research that equips web drama stakeholders with evidence-based guidance for proactively implementing data-driven predictive modeling of audience satisfaction. Such an application has the potential to optimize organizational decision-making, reduces operational uncertainties, mitigate market risks, and foster sustainable development within the Chinese web drama industry.

Second, current literature on audience satisfaction in Chinese web dramas remain insufficient to support evidence-informed policy decision-making by governmental agencies (CNNIC, 2024; Sun, 2024; Yeh, 2023). To enhance the formulation and refinement of relevant laws, policies, and regulations, governmental agencies should be guided by empirical and predictive research on web drama audience satisfaction.

However, relevant governmental agencies face insufficient empirical and predictive research on audience satisfaction in the Chinese web drama industry, limiting their ability to advance evidence-informed formulation and refinement of sector-specific regulations.

For instance, as a major official data source (Stockmann & Luo, 2025), CNNIC (2024) has not yet released relevant data on audience satisfaction in Chinese web dramas. According to Sun (2024), due to insufficient solid and reliable information necessary for drawing precise conclusions, the policy recommendations to official departments have certain limitations. The policies, rules, and regulations governing Chinese web dramas are informed by inadequate empirical research on audience satisfaction as a reference basis (Dai & Zhao, 2024). This research gap may hinder relevant governmental agencies from formulating targeted refinements to existing policies governing Chinese web dramas.

By filling this research gap, this study has the potential to advance policy and regulatory adjustments that support more effective market oversight, promote high-quality content creation and distribution, and contribute to the long-term development of the Chinese web drama industry. Such evidence-informed policy improvements may ultimately enhance audience satisfaction. Meanwhile, the study could support relevant governmental agencies in adopting a big data analytics approach to facilitate evidence-based policy development and contribute to the

gradual improvement of regulatory frameworks within the Chinese web drama industry.

In summary, in response to the research gaps identified above, this study addresses them by developing a comprehensive predictive model of audience satisfaction in Chinese web dramas, informed by the theoretical frameworks of UGT and CCT and implemented through a big data analytics approach. This model endows relevant stakeholders with the capacity to proactively perform data-driven predictive analyses of audience satisfaction, thereby facilitating the implementation of evidence-based targeted interventions tailored to elevate audience satisfaction levels. In doing so, it contributes to addressing the research problems identified in the present study.

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1.4 Research Questions

The main purpose of this study is to develop a comprehensive predictive model of audience satisfaction in Chinese web dramas. This aim requires the integration of five variables: web drama audience satisfaction, web drama viewing motivation, web drama exposure, audience social media engagement, and social media community size. Accordingly, the following research questions will be addressed:

1. Are there the direct effects in the relationships between web drama viewing motivation, web drama exposure, audience social media engagement, and web drama audience satisfaction?

2. Are there the mediating effects of web drama exposure and audience social media engagement in the relationship between web drama viewing motivation and web drama audience satisfaction?
3. Are there the moderating effects of social media community size in the direct relationship between web drama viewing motivation and web drama audience satisfaction, and the association between web drama exposure and audience social media engagement?
4. Are web drama viewing motivation, web drama exposure, audience social media engagement, and social media community size the significant antecedents to develop a predictive model of audience satisfaction of Chinese web drama?

1.5 Research Objectives

The following are the research objectives for this study, which are derived from the research questions above:

1. To examine the direct effects in the relationships between web drama viewing motivation, web drama exposure, audience social media engagement, and web drama audience satisfaction.
2. To investigate the mediating effects of web drama exposure and audience social media engagement in the relationship between web drama viewing motivation and web drama audience satisfaction.
3. To determine the moderating effects of social media community size in the direct relationship between web drama viewing motivation and web drama audience

satisfaction, and the association between web drama exposure and audience social media engagement.

4. To examine whether web drama viewing motivation, web drama exposure, audience social media engagement, and social media community size are the significant antecedents to develop a predictive model of audience satisfaction of Chinese web drama.

Among these research objectives, the first research objective is in line with the first research question, and the second research objective is consistent with the second research question. Meanwhile, the third research objective coincides with the third research question. Ultimately, the fourth research objective is in line with the fourth research question.

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1.6 Significance of the Study

This study holds broad and profound significance for communication research. Specifically, its significance is discussed in four aspects: knowledge significance, theoretical significance, methodological significance, and practical significance, as outlined below.

1.6.1 Knowledge Significance of this Study

First of all, by employing a big data analytics approach to conduct predictive modeling of audience satisfaction in Chinese web dramas, the present study provides

comprehensive and in-depth insights into the antecedents of audience satisfaction. By attaining a comprehensive and in-depth grasp of the antecedents of audience satisfaction in web dramas, stakeholders in the sector can proactively implement targeted interventions to address these antecedents, thereby enhancing audience satisfaction. This strategic approach holds the potential to reduce operational uncertainties, mitigate industry-specific market risks, and facilitate the sustainable development of the Chinese web drama ecosystem.

In the meantime, this study provides rich insights into the mediating effects of web drama exposure and audience social media engagement on audience satisfaction. Concretely, this study provides quantitative research on web drama exposure and audience social media engagement, yielding empirical evidence on their mediating effects. In addition, the current study provides empirical evidence on the moderating effect of social media community size in the context of Chinese web dramas, thereby enriching the understanding of such moderating effects in the social media era.

1.6.2 Theoretical Significance of this Study

There are several theoretical significances of this study. First and foremost, applying UGT to predict audience satisfaction in Chinese web dramas is significant for enriching empirical research on UGT and advancing theoretical development in this domain (McQuail & Deuze, 2020; West & Turner, 2020). Specifically, given that UGT has been infrequently applied in research on web drama audiences (Alhabash et

al., 2024; Chapman & Abraham, 2024; Syafira & Dharmmesta, 2024), this study seeks to adopt UGT to develop a comprehensive predictive model of audience satisfaction in Chinese web dramas. It provides new empirical evidence for UGT research in the big data era, advancing the theory to keep pace with cutting-edge developments in communication research.

More importantly, predictive modeling using a big data analytics approach can introduce emerging technologies and innovative research methods into UGT, thereby facilitating new breakthroughs in the theory's development. When commenting on UGT, McQuail and Deuze (2020) emphasize that it is becoming increasingly difficult to adequately explain audience behavior patterns from a UGT perspective, given the diversification of the media environment.

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Besides that, given that CCT has largely overlooked the complementarity among different forms of new media (Jiang & Liu, 2022; Qin et al., 2023; Wang et al., 2024), the present investigation explores the complementarity of differential new media, specifically examining the interplay between video-sharing platforms and social media from the perspective of CCT. It contributes to enriching empirical research on CCT and advancing its development within the context of complementarity among diverse new media.

The development of the predictive model incorporating the five research variables, which reflects the integration of UGT and CCT, contributes to extending the existing body of knowledge and enhances the practical applicability of these theories within a unified framework. Initially, all interrelationships among the five research variables are theoretically grounded in UGT and CCT. Meanwhile, the mediating effect of social media engagement and the moderating effect of social media community size underscore the integration of UGT and CCT, offering potential for explaining emerging communication phenomena and generating novel insights into web dramas. In addition, the predictive model that integrates the five research variables strengthens the applicability of UGT and CCT in predictive research.

1.6.3 Methodological Significance of this Study

As an emerging research method (Babbie, 2020), the big data analytics approach possesses significant advantages that surpass those of traditional methods, opening new avenues in communication research. By leveraging this approach, the current study can effectively conduct predictive modeling of audience satisfaction in Chinese web dramas. Specifically, the adoption of the big data analytics approach in this research carries the following methodological implications.

First and foremost, the big data analytics approach, widely regarded as a method for studying social behavior without intervention, effectively avoids the *Hawthorne effect* (Babbie, 2020; Boyle & Schmierbach, 2024; Scharrer & Ramasubramanian,

2021). By employing the big data analytics approach, the current study ensures that the audience, as the subject of investigation, remains unobserved and unaffected, thereby enabling their thoughts and behaviors to be captured in a naturalistic setting free from awareness of observation. In this context, the findings and conclusions derived from this study are more likely to be credible. The big data analytics approach leverages the veracity attribute of big data (Castellani & Rajaram, 2021).

Moreover, the big data analytics approach enables efficient collection of large-scale data, providing datasets with higher credibility (Babbie, 2020; Boyle & Schmierbach, 2024; Scharrer & Ramasubramanian, 2021). The big data analytics approach captures the high volume and velocity characteristics inherent in big data (Castellani & Rajaram, 2021; De Mauro et al., 2015). Meanwhile, the big data analytics approach can provide data with relatively high credibility. Through this approach, the data obtained remain unaffected by investigator-induced variations; that is, different researchers can obtain consistent or highly similar results using the big data analytics approach. At the same time, repeated measurements conducted by the same investigator can yield consistent or highly similar data, provided that the investigator adheres to the procedures and protocols of the big data analytics approach. This approach reflects the veracity characteristic inherent in big data (Castellani & Rajaram, 2021).

In addition, the big data analytics approach can ensure that the conclusions drawn are generalizable to the target population (Babbie, 2020; Boyle & Schmierbach, 2024; Scharrer & Ramasubramanian, 2021). As previously stated, new media audiences are so vast, diverse, and widely distributed that data collection through probability sampling is highly challenging. While, reliance on nonprobability sampling often faces the limitation of limited generalizability of the resulting conclusions to the target population. The big data analytics approach circumvents this limitation. It is precisely the high volume and veracity of big data that enable this advantage (Castellani & Rajaram, 2021; De Mauro et al., 2015).

Furthermore, the big data analytics approach significantly expands the research scope of communication studies (Babbie, 2020; Hair et al., 2019). Typically, the population possesses a singular dimension, encompassing entities such as persons, nations, cities, regions, and enterprises (Babbie, 2020; Clark et al., 2022; Scharrer & Ramasubramanian, 2021). Nonetheless, big data analytics approach can produce the unprecedented quantifiable dimensions for human existence (Mayer-Schönberger & Cukier, 2013). Thus, it brings to the great expansion of communication research scope. As mentioned by Castellani and Rajaram (2021) and Hair et al. (2019b), the type and scope of researches that were rarely imagined before have been revolutionized by virtue of big data. The big data analytics approach reflects the characteristic of variety inherent in big data (Castellani & Rajaram, 2021).

1.6.4 Practical Significance of this Study

This study holds multiple practical significances. First, the predictive model developed in this study, along with the predictive equation derived from it through conditional process analysis (Hayes, 2022; Igartua & Hayes, 2021), enables Chinese web drama stakeholders to timely conduct proactive, data-driven predictive analysis of audience satisfaction, thereby facilitating evidence-based targeted interventions to enhance audience satisfaction.

Specifically, for stakeholders in the Chinese web drama industry, this study offers tangible, evidence-based guidance to address operational challenges and seize market opportunities. First, it enhances decision-making efficiency: by providing a data-driven tool for forecasting audience satisfaction, the study enables stakeholders to allocate resources more effectively, including prioritizing high-potential content themes and refining marketing campaigns, while mitigating operational uncertainties associated with market volatility. Second, it contributes to mitigating market risks: the model's ability to predict satisfaction trends helps stakeholders anticipate shifts in audience preferences, enabling preemptive adjustments to content offerings and reducing the likelihood of costly misalignments between production decisions and audience demands.

In addition, the scholarly evidence on Chinese web dramas generated by this study can serve as a valuable reference for government authorities in formulating and

refining laws, policies, and related regulations, thereby contributing to more informed and effective public decision-making. Currently, governmental authorities in China are in the process of drafting the *Radio and Television Law of the People's Republic of China*. This legislative initiative explicitly establishes the principle of integrated regulation for web dramas and traditional radio and TV programs. With regard to web drama policies, China implements a mandatory distribution licensing system and a prior review mechanism. The findings of this study may provide useful insights for improving and enriching the draft legislation.

By leveraging the insights generated from this study, relevant governmental authorities may consider refining existing policies related to Chinese web dramas. Such policy adjustments could support more effective market oversight, promote the creation and distribution of higher-quality content, and contribute to the long-term development of the industry, which may in turn help improve audience satisfaction. Meanwhile, relevant governmental authorities could adopt a big data analytics approach to conduct systematic evaluations of the web drama industry, which may support evidence-based policy development and contribute to the gradual improvement of regulatory frameworks.

1.7 Conceptualization of the Construct

Conceptualization is defined as the psychological process through which vague and imprecise ideas are transformed into concrete and precise concepts (Babbie, 2020).

This study includes five variables: web drama audience satisfaction, web drama viewing motivation, web drama exposure, web drama audience's social media engagement, and social media community size. The conceptual definitions of these constructs are elaborated individually below.

1.7.1 Web Drama Audience Satisfaction

This study defines web drama audience satisfaction as the degree of psychological or emotional fulfillment resulting from web drama audiences' prior viewing expectations and their actual viewing experiences.

1.7.2 Web Drama Viewing Motivation

This study defines web drama viewing motivation as the psychological driving force that prompts individuals to engage with web drama content, which arises from the need to fulfill requirements including entertainment, relaxation, escapism, time passing, information seeking, and social interaction, thereby encouraging active involvement in media consumption.

1.7.3 Web Drama Exposure

This study defines web drama exposure as the extent to which audiences actively seek out, encounter, and engage with specific web drama content or thematic categories through video-sharing platforms.

1.7.4 Web Drama Audience's Social Media Engagement

This study defines web drama audience's social media engagement as active participation in which audience members voluntarily create, share, and consume web drama-related content through social media to express opinions or emotions, driven by motivational factors.

1.7.5 Social Media Community Size

The present study defines social media community size as the total number of social media entities that engage in sustained interactions centered on a common element of interest within a group in a social media network.

1.8 Scope of the Study

The aim of this study is to develop a comprehensive predictive model of audience satisfaction in Chinese web dramas by integrating big data analytics with theoretical frameworks from UGT and CCT. To achieve this aim, the analysis focuses on all Chinese web dramas with accessible big data from six major video websites in China: Tencent Video, iQIYI, Youku, Mango TV, Bilibili, and SOHU Video.

Since 2018, Chinese web dramas have undergone substantial development and a notable rise in popularity (Hu, 2021; Zhou & Zhi, 2020). As a result, the analysis incorporates Chinese web dramas with accessible big data collected from 2018 to the present (as of August 15, 2024). Furthermore, by leveraging a big data analytics

approach, this study enables access to real-time statistical datasets, including those derived from large-scale social media comments, social media metrics, major search engines, and professional big data platforms, thereby measuring audience satisfaction, motivation and behavior for each web drama.

In summary, the scope of this study is delimited in four aspects. Temporally, it focuses on Chinese web dramas premiered from 2018 to the present (as of August 15, 2024). Platform-wise, this study is confined to all Chinese web dramas with accessible big data from six major platforms: Tencent Video, iQIYI, Youku, Mango TV, Bilibili, and SOHU Video. From a data perspective, this study draws on real-time statistical datasets derived from large-scale social media comments, social media metrics, major search engines, and professional big data platforms. Regarding research subjects, this study examines audience satisfaction and its antecedents in relation to Chinese web dramas. This delimitation ensures the feasibility and analytical depth of the research.

1.9 Organization of the Thesis

This thesis is organized into five chapters. Chapter One provides a general introduction and overview of the study. Chapter Two reviews the relevant literature, presenting the theoretical framework, research hypotheses, conceptual model, and hypothesized predictive model. Chapter Three outlines the research methodology employed, while Chapter Four presents the findings and in-depth analysis of the

results. Finally, Chapter Five discusses the implications of the study and draws the main conclusions.

1.10 Chapter Summary

This chapter provides an introduction to the study. Specifically, it consists of eleven sections. After introducing the chapter in the first section, the second section presents the research background. The third section then states the problem statement. Next, the fourth and fifth sections present the research questions and objectives, respectively. The sixth section highlights the significance of the study. In addition, the seventh section outlines the conceptualization of all constructs. Furthermore, the eighth section defines the scope of the study. The ninth section describes the organization of the thesis, followed by the tenth section, which summarizes the chapter.

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CHAPTER TWO

LITERATURE REVIEW

2.1 Introduction

This chapter provides a rigorous review of the literature on Chinese web dramas, foreign web dramas, audience satisfaction, viewing motivation, media exposure, social media engagement, social media community size, media effects, and the social media big data analytics approach. Meanwhile, UGT and CCT are reviewed as key components of the study's theoretical framework. Based on the literature review, this research develops a conceptual model and proposes eleven research hypotheses. Finally, the hypothesized predictive model is formulated based on this conceptual model.

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2.2 Review of Literature

2.2.1 Chinese Web Drama

Web drama, also known as Internet drama, web series, or online series, is a new form of audio-visual program distributed via the Internet (Mi et al., 2022). According to the current literature, research on Chinese web dramas encompasses studies on concept, nature, production, content, market, audience, and policy, which are reviewed separately below.

2.2.1.1 Concept of Chinese Web Drama

According to Feng (2016), the concept of Chinese web drama encompasses both broad and narrow definitions. In the broad sense, it refers to all Chinese serials distributed through Internet media. In the narrow sense, Chinese web drama denotes a specific type of Chinese audio-visual program produced exclusively for online platforms (Feng, 2016; Zhang, 2016). Such programs utilize the Internet as their primary communication channel, adopt video websites as the main broadcasting platform, and center on narrative storytelling as their core content (Feng, 2016; Zhang, 2016).

Cao et al. (2023) propose that web dramas represent a new form of TV programming that primarily utilizes the Internet as its distribution medium, targets online users as its core audience, and is characterized by high levels of audience interactivity, aiming to enhance dissemination effectiveness through the fulfillment of audience needs. Moreover, according to Hu (2021), Mi et al. (2022) and Wang (2022), web dramas are serialized productions that primarily utilize the Internet as their distribution medium, specifically, they are built upon Internet technologies, target online users as their primary potential audience, and attempt to satisfy audiences' needs for entertainment, relaxation, escapism, passing time, information seeking, and social interaction through compelling and immersive narratives. This study adopts the concept from Hu (2021), Mi et al. (2022), and Wang (2022) due to its comprehensiveness and its relevance to the research topic of this study.

2.2.1.2 Nature of Chinese Web Drama

Web dramas offer numerous advantages. They are less expensive and easier to launch compared to traditional films or TV programs (Keltie, 2017), a characteristic that also holds true for Chinese web dramas (Hu, 2021; Wang, 2022). Additionally, Chinese web dramas provide greater creative flexibility and have fewer ties to financial institutions or broadcasters, enabling them to feature programming that major networks might find difficult to justify to advertisers or conservative stakeholders (Hu, 2021; Keltie, 2017; Wang, 2022). These characteristics allow Chinese web dramas to expand the possibilities for producing diverse content, positioning them as innovative cultural products and significant communication phenomena with profound historical implications, revitalizing the mass culture market (Cao et al., 2023; Keltie, 2017; Yang, 2023).

Concurrently, Chinese web dramas are highly shareable due to their online delivery format (Hu, 2021; Monaghan, 2017; Wang, 2022). Moreover, as Chinese web dramas are distributed through video websites, audiences can access them anytime via computers, mobile phones, or tablets, demonstrating that web drama viewing is more convenient and flexible (Hu, 2021; Wang, 2022). In addition, audience interaction through live subtitles and comments in the message section highlights the vitality and dynamism of web dramas (Hu, 2021; Monaghan, 2017; Wang, 2022).

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2.2.1.3 Production of Chinese Web Drama

Compared to traditional film or TV production, web drama production entails lower costs and requires fewer resources for launch, making it a more accessible and scalable medium for content creators (Keltie, 2017). According to Tan and Yuan (2021), the production process of Chinese web dramas can generally be divided into three distinct stages. The first stage encompasses thematic planning and scriptwriting, which are systematically executed to establish a solid foundation for web drama development (Tan & Yuan, 2021). Next, on-site shooting proceeds concurrently with key video production processes such as footage editing, color correction, and sound design (Tan & Yuan, 2021). In the final phase, the release of Chinese web dramas is systematically carried out (Tan & Yuan, 2021).

Moreover, Yang and Tang (2024) emphasize that advantages such as institutional support from government authorities and collaborative efforts among multiple film and TV enterprises during production can contribute to a strong synergistic effect in the creation of high-quality web dramas. Additionally, according to Wang (2022), the advancement of media technology has elevated the production of web dramas to a higher level of sophistication and efficiency. The innovative approaches to special effects production have become a driving force behind the flourishing landscape of Chinese web drama creation (Wang, 2022).

In recent years, scholarly research has increasingly emphasized the transformative role of big data and artificial intelligence (AI) in shaping the production of Chinese web dramas. As stated by Kong (2020), audience big data analysis can provide precise support for decision-making in optimizing web drama production. In response to the emergence of certain low-quality web dramas, the production of web dramas urgently requires optimization (Kong, 2020). Web drama producers can leverage big data technologies to collect big data from platforms such as Douban, WeChat, and major video streaming sites (Kong, 2020). By systematically organizing and conducting visualized analysis of this data, they could gain clear insights into the specific issues and weaknesses present in individual productions, thereby facilitating the advancement of web dramas toward a more refined and high-quality trajectory (Kong, 2020).

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In addition, AI has significantly enhanced the production efficiency and quality of Chinese web dramas. According to Zhang and Zhang (2023), AI has significantly empowered the production of web dramas, exerting a profound influence across multiple stages of the web drama industry chain. Their findings indicate that, in the early development phase, AI can be applied to box office forecasting, scriptwriting, and storyboarding. During the shooting and production phase, it can be utilized in special effects generation, automated editing, image enhancement, and motion capture, thereby enhancing both production quality and efficiency. In the distribution stage, AI can support user profiling and market analysis, offering robust capabilities

for precise audience targeting. Besides that, according to Yang et al. (2025), AI-driven micro-web dramas have emerged on digital platforms such as Douyin and Bilibili. The authors point out that by using AI technologies such as AI-driven art and video editing, these micro-web dramas integrate traditional cultural symbols with contemporary visual styles, thereby achieving closer alignment with audience preferences and viewing behaviors.

2.2.1.4 Content of Chinese Web Drama

According to Yang (2023), Chinese web dramas exhibit diverse content, covering romance, martial arts, idol series, family drama, youth stories, urban life, comedy, war, military, detective drama, suspense, crime, and time-travel drama. Compared to traditional TV series, the content of Chinese web dramas features faster pacing, stronger character conflicts, and a greater focus on entertainment (Yang, 2023). Their content is increasingly drawn from digital popular culture, especially serialized web novels (Yang, 2023).

Moreover, Yang (2023) points out that the diversity in content observed in web dramas can primarily be attributed to the growing audience base, the expansion of the digital market, and increasingly fierce competition among production companies. Furthermore, The diversity of content enables the creation of highly segmented markets, effectively catering to the varied preferences of distinct audience segments,

thereby positively contributing to the development of competitive branding among web drama producers (Yang, 2023).

In recent years, research on Chinese web drama content has increasingly emphasized high-quality production, driving the trend toward content refinement and industrial upgrading. By examining the Chinese web drama *The Longest Day In Chang'an*, Dai (2020) and Wang (2022) highlight how Chinese excellent traditional culture serves as a rich source of content for Chinese web dramas. Furthermore, many high-quality Chinese web dramas effectively convey the depth and richness of this cultural heritage through compelling themes, intricate narratives, and well-developed character portrayals (Dai, 2020; Wang, 2022).

Taking the Chinese web drama *beginnings* as a case in point, Zeng (2022) points out that high-quality web dramas should focus on and reflect real-life experiences, portray the living conditions of diverse social strata, critically examine negative social phenomena, and convey positive social values. In addition, Cao et al. (2023) conduct an in-depth analysis of the youth-oriented web drama *with you*, the suspense web series *day and night*, and the crime-themed web drama *under the skin*, revealing that high-quality web dramas are characterized by realistic storytelling, meticulous attention to detail, and the consistent conveyance of positive values in their content.

Besides that, social media platforms are increasingly serving as important spaces for web drama audiences to engage in content-related sharing and discussions. Zhang and Liang (2024) argue that while watching Chinese web dramas, audiences simultaneously engage with social media to share and discuss content, giving rise to a second-screen phenomenon. The authors illustrate this with an example: following the release of the web drama *Love Between Fairy and Devil*, audience interaction on Weibo increased significantly, with related topics accumulating over 26 billion views.

2.2.1.5 Market of Chinese Web Drama

Compared to TV dramas, web dramas are widely regarded as possessing higher commercial profitability and greater market potential, and they have the capacity to generate synergistic economic effects that extend to interconnected cultural industries, including tourism, TV, and online comics (Kang, 2021b). According to Dong (2021), the profitability of Chinese web dramas is primarily driven by paid viewing and advertising revenue. On major platforms such as iQIYI, Tencent Video, and Youku, over 90% of web dramas are available exclusively through paid access. At the same time, the advertising sector related to web dramas has generated revenues exceeding 20 billion RMB. Together, these trends highlight the growing monetization potential of high-quality content in the digital streaming landscape.

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In recent years, amid intense market competition, research on the Chinese web drama market has increasingly focused on market segmentation, the role of social media in audience engagement, cost reduction for enhanced efficiency, and overseas market expansion. First, according to Ji (2023), the Chinese web drama market has experienced notable segmentation in recent years, driven by increasingly diversified viewer preferences and the widespread adoption of platform-specific strategies across video streaming services. Meanwhile, CNRTA (2024) highlights that driven by market segmentation strategies in the web drama industry, video platforms are actively releasing web dramas aligned with their respective brand positioning and target audience profiles. For instance, iQIYI tends to release web dramas centered on romance, suspense, and realistic themes, while Tencent Video favors content featuring adventure, fantasy, and science fiction genres (CNRTA, 2024).

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At the same time, Ji (2023) points out that web drama audiences actively share and discuss content on social media platforms, thereby expanding the niche segments of the web drama market. However, this has simultaneously given rise to negative outcomes, namely, audiences in segmented markets selectively filter web drama content, leading individuals to focus primarily on topics and content of personal interest, thereby reinforcing the *Information Cocoons* phenomenon (Ji, 2023).

Moreover, Ji (2023) argues that the major streaming platforms have adopted a strategy of cost reduction and revenue optimization, aiming to maximize returns

through minimal investment in the Chinese web drama market. According to CNRTA (2024), since 2022, against the backdrop of the web drama industry's emphasis on cost reduction and efficiency enhancement, the overall volume of Chinese web dramas has declined. Most video platforms have adopted exclusive broadcasting strategies to strengthen their market competitiveness (CNRTA, 2024).

Additionally, the Chinese web drama market has expanded into overseas markets in recent years. Zhou and Zhi (2020) find that the strategic development of Chinese web dramas has gradually shifted from domestic to international markets, with continuous improvements in production quality and an expanding global influence, reflecting a positive trend of innovative growth within a stable framework.

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2.2.1.6 Audience of Chinese Web Drama

Existing research on audiences of Chinese web dramas is organized into four thematic categories: audience agency and cultural participation, audience motivations and aesthetic preferences, data-driven audience analysis, and comparative insights from overseas digital video platforms. The following discussion synthesizes key findings within each category to provide a comprehensive overview of current scholarly understanding.

Regarding audience agency and cultural participation, Wang (2019) analyzes the popular web drama *Guardian* and argues that media fandom studies have

demonstrated how fans actively engage in subversive resistance against mainstream ideology from a cultural studies perspective. Building on this, Chen and Ren (2019) emphasize that audiences are no longer passive recipients but have become influential actors in production, distribution, and interactive processes, necessitating that Chinese web dramas prioritize audience feedback and adapt to evolving demands. Similarly, Wang (2022) introduces youth subculture theory into the study of viewing practices, arguing that Chinese web dramas play an active role in shaping a distinct youth subculture among young viewers.

On audience motivations and aesthetic preferences, Song (2020) identifies accessibility and adaptability as key factors attracting audiences with significant market potential. Current preferences lean toward suspense and detective genres, though comedies may gain traction in the future. Expanding on this, Su (2022) proposes that audience aesthetic demands operate across audio-visual, psychological, and cultural dimensions, suggesting that the development of Chinese web dramas should be guided by these audience-driven needs. Hu (2021) further examines audience characteristics through textual analysis, comparing differences in viewing platforms, media usage patterns, and content selection preferences within contemporary social contexts.

In terms of data-driven audience analysis, Zhou and Zhao (2021) employ big data analytics to examine audience responses to audio-visual content in China. Their

study develops an indicator system to investigate how specific metrics influence audience ratings. It further reveals that audiences exhibit stronger dependency on dominant digital platforms, particularly social media, when engaging with web dramas. By analyzing user-generated data, the research demonstrates how big data can illuminate audience motivations, emotions, and behavioral patterns. Mi et al. (2022) develop a predictive model for web drama viewership using comment sentiment analysis and an improved stacking ensemble approach. Their findings show that incorporating sentiment scores significantly enhances the model's predictive performance, demonstrating the value of big data analytics in understanding audience behavior.

With regard to audience from overseas video platforms, several studies offer insightful parallels. Maulana (2020) finds that for audiences of the YouTube channel Rans Entertainment, product quality directly and positively affects both corporate image and customer satisfaction, while corporate image in turn enhances satisfaction and loyalty. Customer satisfaction is also shown to directly increase loyalty. Similarly, Jung and Hwang (2023) identify usefulness and enjoyment as two key features of YouTube that positively influence customer satisfaction. The study further reveals that satisfaction promotes both the intention to revisit and the intention to exchange information, with the former reinforcing the latter. Additionally, Han et al. (2023a) examine web talk show documentaries and find that self-transcendence themes are positively correlated with audience satisfaction and

consistently contribute to higher satisfaction levels.

2.2.1.7 Policy of Chinese Web Drama

China's National Radio and Television Administration (CNRTA) issued a notification on further standardizing the planning, filing, and content review of TV dramas, web dramas, and web movies (CNRTA, 2023). This notification clarifies broadcasting requirements for web dramas and emphasizes the need to regulate productions with excessive padding while curbing exorbitant remuneration for performers (CNRTA, 2023).

Additionally, according to CNNIC (2024), the government actively formulates and improves policies, rules, and regulations to strengthen the supply of high-quality content and foster a healthy content ecosystem. At the same time, policy initiatives encourage the continuous advancement of web drama industrialization, promoting cost reduction and efficiency improvement across the industry (CNNIC, 2024). From a policy perspective, Sun (2024) analyzes the reasons why the web drama *Ruyi's Royal Love in the Palace* underperformed in the market, offering targeted recommendations to regulatory authorities and producers for improving future outcomes.

These Chinese web drama studies above enable researchers to gain a broad and in-depth understanding of web dramas within the context of the new media era,

offering valuable insights for their development. However, several limitations remain. First, research on web drama audience satisfaction remains limited. This gap may be attributed to the field's relative novelty, as scholarly inquiry is still in the exploratory stage. Second, audience studies often rely on case-specific analyses, such as single-drama examinations like *Guardian*, which may restrict the generalizability of findings. Third, there is a notable imbalance in geographic and demographic focus, with most studies centering on urban, younger, and digitally connected populations, leaving rural, older, or less tech-savvy audiences underrepresented.

These gaps collectively hinder the comprehensiveness and representativeness of research on Chinese web drama audiences. Therefore, by leveraging big data analytics, this study contributes to predictive modeling of audience satisfaction in Chinese web dramas. The big data analytics approach enables access to real-time, large-scale datasets derived from social media comments, platform metrics, major search engines, and professional big data platforms, thereby facilitating more comprehensive and dynamic audience analysis.

2.2.2 Foreign Web Drama

Although this study focuses on Chinese web dramas, research on foreign web dramas also offers certain reference value. Therefore, this section provides a brief literature review of international web drama studies. Leder (2021) notes that in Australia, web dramas have become commonplace and are now regarded as a distinct art form,

supported by the emergence of local and international web drama awards and a viewer preference for web dramas over traditional screen media such as TV and film. According to Dhiman and Malik (2021), web dramas are increasingly replacing TV in India, where they have gained significant popularity in recent years due to technological advancements and viewing convenience. Major platforms such as Amazon, Netflix, and SonyLIV have invested heavily in regional content production (Dhiman & Malik, 2021).

At the same time, Kang (2021b) asserts that Korean web dramas are a form of short, serialized content specifically designed for mobile viewing platforms. Kang (2021b) further argues that they are regarded as a higher-quality medium than traditional TV dramas due to their greater economic potential and ability to illuminate the relationship between perceived quality and commercial profitability. As prominent web drama platforms, Netflix and YouTube have been examined by Havens and Stoldt (2023) and Cunningham et al. (2023). Havens and Stoldt (2023) point out that Netflix cultivates a corporate brand reflecting the extensive variety of programming it offers, enabling it to compete with rival subscription-based streaming services.

Cunningham et al. (2023) argue that YouTube serves as a foundational platform for the convergence of social media and TV, based on an analysis of India, Brazil, and Australia. They suggest that the future trajectory of TV may diverge significantly from its developmental path in the United States (Cunningham et al., 2023). The

above literature on foreign web dramas offers valuable reference and inspiration for the study of Chinese web dramas.

However, audience satisfaction remains understudied within this body of international web drama research. Moreover, existing studies tend to focus on macro-level industrial trends or platform strategies, often overlooking granular audience-level factors such as emotional engagement. Furthermore, while data-driven methods are increasingly adopted, many studies still rely on qualitative case studies or descriptive accounts, limiting generalizability. Future research should integrate mixed-method approaches and leverage large-scale user data to deepen understanding of audience satisfaction and behavioral dynamics in the global web drama landscape.

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2.2.3 Audience Satisfaction

According to Oliver (2015), satisfaction denotes a consumer's evaluative response, specifically a judgment that a product or service attribute, or the product or service as a whole, delivers a satisfying level of consumption-related gratification. In the context of communication research, Dennis and Gray (2013) define audience satisfaction as the TV audience's evaluative response to the viewing experience or a specific aspect thereof.

In addition, according to Ghorbanzadeh and Rahehagh (2021), satisfaction refers to the emotional evaluation consumers form toward a specific product or service, or the degree of pleasure derived from the associated experience. Moreover, Lee (2023) defines viewing satisfaction as the degree of psychological and emotional fulfillment experienced by audiences when watching a program. Additionally, Li (2024) argues that audience satisfaction denotes a psychological state derived from audiences' prior viewing expectations and their actual viewing experiences.

The definitions from Oliver (2015) and Dennis and Gray (2013) emphasize that audience satisfaction is an evaluative response formed by audiences in relation to their viewing experience, yet they do not explicitly address the dimension of psychological or emotional state. Although the definitions proposed by Ghorbanzadeh and Rahehagh (2021) and Lee (2023) emphasize audience satisfaction as a measure of psychological and emotional fulfillment, they overlook the role of audiences' prior viewing expectations in shaping satisfaction. In contrast, Li (2024) fails to recognize that satisfaction constitutes an evaluative response. Drawing on the definitions above, this study defines web drama audience satisfaction as follows: The degree of psychological or emotional fulfillment derived from web drama audiences' prior viewing expectations and their actual viewing experiences.

Through systematic categorization and analysis, the literature on audience satisfaction is organized into four main domains based on factors influencing

audience satisfaction: individual-related factors, media-related factors, technology-related factors, and content-related factors. These domains are discussed below.

Regarding individual-related factors, Mahdieh and Yakhkeshi (2022) conclude that both film features and viewer orientation have a positive impact on film audience satisfaction. Moreover, lifestyle, as a dimension of viewer orientation, significantly influences film audience satisfaction. The findings from Ng et al. (2022) indicate that perceived serendipity, presentation quality, and social presence in livestream shopping enhance customer satisfaction and cognitive integration through consumer values. The findings from Ng et al. (2022) can assist practitioners in designing more effective strategies for livestreaming e-commerce.

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Moreover, Sukendi et al. (2023) seek to identify the factors influencing Korean drama audience satisfaction and conclude that satisfaction is positively influenced by the attractiveness and credibility of actors and actresses as well as by audience involvement, while it is negatively affected by the connectedness between the audience and the surrounding characters and settings. Taking *Going Seventeen* as an example, Limic and Limb (2023) aim to identify the production components unique to self-produced web entertainment programs. Their findings show that components such as artist participation, content creativity, and editing style positively influence

program satisfaction and enhance artist loyalty, except for the artist-producer relationship.

With regard to media-related factors, Huang et al. (2023) argue that, from the perspective of media richness theory, the informativeness and convenience of livestreaming platforms significantly influence audience satisfaction and flow experience, thereby affecting media loyalty. In the meantime, Jung and Hwang (2023) find that two attributes of YouTube, usefulness and fun, positively influence user satisfaction. In turn, these findings indicate that user satisfaction positively affects both revisit intention and willingness to share information. The study by Genggong and Tawai (2024) aims to identify web media audience satisfaction in Southeast Sulawesi. Their findings indicate that audiences in this region report high levels of satisfaction across several dimensions: enjoyment in accessing information, particularly local news; the ability to build rapport with content; using information as a basis for decision-making; and exposure to entertaining elements during information searches.

With repect to technology-related factors, Guan (2023) leverages big data technology to investigate animation and examines the impact of new media technology on animation. According to Guan (2023), the utilization of new media technologies could enhance visual effects, plot and content quality, character modeling, color design satisfaction, and audience viewing enjoyment. Moreover, Ahmed and

Abdulkareem (2023) argue that big data analysis is essential for enhancing audience satisfaction. By leveraging a big data analytics approach, entertainment corporations personalize recommendations based on audience behavior, interests, and historical data, thereby improving audience satisfaction (Ahmed & Abdulkareem, 2023).

Regarding content-related factors, Maulana (2020) finds that product quality exerts a substantial positive and direct impact on business image and customer satisfaction. In addition, Maulana (2020) points out that business image has a significant positive and direct influence on customer satisfaction and loyalty, and that customer satisfaction positively and directly affects loyalty. Meanwhile, Kim and Kim (2020a) argue that viewing satisfaction on media and programs stems from expectations regarding content; consequently, when viewers' expectations for a program are fulfilled, their level of satisfaction is shaped. In other words, viewing satisfaction reflects the fulfillment of audience desires.

In addition, Han et al. (2023a) examine how audience satisfaction on web talk shows is influenced by themes of self-transcendence in web talk show documentaries, revealing a positive correlation between self-transcendence themes and audience satisfaction. In other words, audiences consistently express higher satisfaction with web talk show documentaries that explore such themes.

Previous studies on audience satisfaction exhibit a diversified trend and have yielded fruitful results. Among them, certain studies such as those by Kim and Kim (2020a) and Ng et al. (2022) provide valuable references for this study. However, web drama audience satisfaction has received limited attention in communication research, particularly regarding the antecedents of satisfaction in the context of Chinese web dramas.

Moreover, insufficient studies on audience satisfaction have examined the simultaneous impact of two or more new media platforms, despite the growing need to recognize and investigate such influences in the new media era. Furthermore, prior research on audience satisfaction has largely overlooked the use of big data analytics, which hinders innovative advancements in audience satisfaction research in the digital age. Accordingly, this study selects web drama audience satisfaction as the dependent variable and aims to develop a predictive model for Chinese web drama audience satisfaction by simultaneously examining the effects of video websites and social media.

2.2.4 Viewing Motivation

In psychological research, motivation is defined as a driving force or forces in charge of the initiation, tenacity, direction, and vigour of goal directed behaviour, it consists of the biological drives and social forms of motivation (Colman, 2015). Moreover, based on need-hierarchy theory authored by Maslow, motivation is the internal

driving force for human survival and growth, composed of differential needs (Zhang, 2019).

Closer to communication research, viewing motivation is defined as the reasons or specific purposes underlying the consumption of media content (Winderman & Smith, 2016). Meanwhile, according to Lee et al. (2018), viewing motivation refers to the psychological drivers that prompt individuals to engage with media content, arising from the need to satisfy specific requirements, thus encouraging active involvement in media consumption. Besides that, Hu (2021) and Wang (2022) propose that the primary motivations for viewing web dramas include entertainment, relaxation, escapism, passing time, information seeking, and social interaction.

Both the definitions proposed by Colman (2015) and Zhang (2019) emphasize viewing motivation as a driving force, thereby serving as a valuable reference for this study. In the meantime, the definition from Winderman and Smith (2016) does not sufficiently highlight the crucial role of fulfilling audience needs in driving media engagement. In contrast, this definition proposed by Lee et al. (2018) not only highlights viewing motivation as a psychological driving force but also clarifies its interrelationship with media exposure and the fulfillment of audience needs, making it a comprehensive and theoretically sound concept. Therefore, this study defines web drama viewing motivation as the psychological driving force that prompts individuals to engage with web drama content, which arises from the need to fulfill

requirements including entertainment, relaxation, escapism, time passing, information seeking, and social interaction, thereby encouraging active involvement in media consumption.

Based on UGT, the terms "motivation" and "need" can be regarded as conceptually equivalent, with largely overlapping meanings (McQuail & Deuze, 2020). Consequently, viewing motivations in this study are understood as stemming from viewers' underlying needs. Through systematic categorization and review, the literature on viewing motivation research can be broadly divided into three main areas: studies focusing on reality TV shows, TV dramas, and web-based videos.

Regarding reality TV shows, Vijay Kumar and Arulchelvan (2015) investigated the viewing motivations and impacts of reality TV shows, finding that the opportunity to showcase talented individuals is the primary motivation for watching such programs. Additionally, Kim and Kim (2020a) conducted a survey and concluded that there are five viewing motivations for travel reality shows: entertainment, information-seeking, socializing, habitual time-spending, and vicarious gratification. Moreover, presence (viewing experience) mediates the effect of these motivations on viewer satisfaction.

Regarding TV dramas, Keshishian and Mirakyan (2017) investigated the viewing motivations for soap operas, a prominent cultural phenomenon among college students, by examining the relationship between students' reported motivations and

their demographic characteristics. Their study identified three primary viewing motivations for soap operas, among which “passing time” was particularly prevalent among students from provincial regions. Moreover, Shi and Wang (2019) developed a two-stage structural model that distinguishes between two TV drama viewing motivations: viewers’ fondness for a drama and the need for cognitive closure. They found that both motivations positively influence TV drama viewing behavior.

In addition, in response to the popularity of Indian soap operas in Turkey, Yücel and Çapraz (2022) examined the viewing motivations of female audiences and identified five key motivations among Turkish women for watching Indian soap operas. The findings indicate that participants’ willingness to embrace traditional lifestyles, their perceived notions of female empowerment, and their favorable attitudes toward maintaining social order directly influence their viewing behavior.

Regarding web-based videos, Steiner and Xu (2018) explored the changes in binge-watching motivations among streaming video audiences and found that cultural inclusion, sense of completion, catching up, relaxation, and improved viewing experience are the primary motivations for binge-watching. Investigating the uses and gratifications of audiences derived from web streaming technologies during the COVID-19 pandemic, Camilleri and Falzon (2020) revealed that the perceived utility and ease of use of web streaming services are significant antecedents of audiences’ motivations to utilize these technologies. Furthermore, they point out that

usage motivations for web streaming technology stem from audiences' needs for information and entertainment.

Building on UGT, Ham and Lee (2020) examined the usage motivations of live streaming services as well as the variables affecting audiences' viewing behavior in live streaming. Their investigation revealed that the six motivations for V Live (a live-streaming service) usage include interpersonal association motive, social presence motive, celebrity support motive, celebrity presence motive, social contacting motive, and distinction motive (Ham & Lee, 2020). Omar and Dequan (2020) investigated how consumers' motivations and personality variables influence integrated TikTok usage behavior. Their findings indicate that audience motivations, specifically self-expression, archiving, escapism, and social interaction, are significant determinants of TikTok usage behavior.

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Moreover, Jin et al. (2023) assert that the satisfaction of Malaysian university students with Instagram usage is positively influenced by specific motivations, including cognitive needs, affective needs, personal integrative needs, and social integrative needs. Additionally, Dong and Xie (2024) investigated the short video audience's motivations for using Chinese TikTok, stating that motivation is crucial for understanding audience engagement. They point out that there are six motivations for viewing short videos: exploratory behavior toward novelty, habit maintenance, relationship maintenance, stress relief, time passing, and escape from reality.

Meanwhile, Du et al. (2024) analyzed the usage of TikTok by college students and concluded that the main demands for TikTok usage include informational, social, entertainment, convenience, and integrative needs at both individual and social levels. Furthermore, they highlighted that the most significant demand among college students is entertainment, whereas the least significant is information (Du et al., 2024). On top of that, according to Hu (2021) and Wang (2022), web dramas are built on Internet technologies, target online users as their primary audience, and aim to fulfill audiences' needs for entertainment, relaxation, escapism, passing time, information seeking, and social interaction through compelling and immersive narratives.

The literature above examines various audio-visual programs, including reality TV shows, TV dramas, and web-based videos, and reveals that viewing motivations differ significantly across program genres. Specifically, audiences are driven by distinct motivational factors, reality TV shows are primarily associated with motivations such as entertainment, information-seeking, socializing; TV dramas are linked to motivations such as time-killing, fondness for a drama and the need for cognitive closure; and web-based videos are characterized by motivations including stress relief, time passing, and escapism.

The literature above are devoted to empirical research on various audio-visual programs, contributing to the enrichment of knowledge regarding viewing motivations in these media. Especially, Hu (2021) and Wang (2022) propose that the primary motivations for viewing web dramas include entertainment, relaxation, escapism, passing time, information seeking, and social interaction. They offer substantial literary support for further research on web drama viewing motivations. However, it can be observed that viewing motivation research remains inadequate in the context of Chinese web dramas, resulting in challenges for researchers in keeping pace with the evolution of web dramas. Notably, the relationship between viewing motivation and audience satisfaction remains unclear in the existing literature on Chinese web dramas, warranting further investigation.

According to UGT, the social and psychological origins of needs lead to differential media exposure (or engagement in alternative activities), resulting in need gratification and other outcomes (McQuail & Deuze, 2020; Katz et al., 1974; West & Turner, 2020). Building on this, this study employs web drama viewing motivation as the independent variable to achieve the research aim. Meanwhile, the primary motivations for viewing web dramas include entertainment, relaxation, escapism, passing time, information seeking, and social interaction (Hu, 2021; Wang, 2022). Large-scale social media comments reflecting these viewing motivations should be systematically collected and analyzed. This will help examine whether viewing motivations function as antecedents of audience satisfaction in the context of Chinese

web dramas, thereby supporting the development of predictive models for audience satisfaction.

2.2.5 Media Exposure

According to Slater (2004), media exposure is defined as the degree to which audience members have been exposed to specific messages or categories of media content. At the same time, Slater (2004) asserts that the exposure refers to an individual's merely encountering the messages, regardless of whether they are sufficiently noted to stick in memory. Moreover, Wu and Li (2017) define media exposure as individuals' access to media content through both traditional and new media platforms.

In addition, according to De Vreese and Neijens (2016), media exposure refers to the process by which individuals are exposed to a diverse range of media content across an increasing number of platforms, leading to differential media effects. Besides that, referring to definition from Ning et al. (2022), media exposure is defined as the degree to which users have encountered related information.

Among the definitions above, the definitions proposed by Slater (2004) and Ning et al. (2022) emphasize the degree of exposure, a dimension that is particularly significant within the context of a big data analytics approach. Meanwhile, Wu and Li (2017) emphasize the media platforms on which audiences have encountered

relevant information. Additionally, audiences are conceived as active individuals who purposefully seek out and utilize media within the framework of UGT (McQuail & Deuze, 2020; Katz et al., 1974; West & Turner, 2020). Drawing on the definitions proposed by Ning et al. (2022), Slater (2004), and Wu and Li (2017) as well as UGT, this study defines web drama exposure as the extent to which audiences actively seek out, encounter, and engage with specific web drama content or thematic categories through video-sharing platforms.

Over the past few decades, research on media exposure has attracted sustained scholarly attention (Tao & Zhang, 2022). Building on knowledge graph methodologies, Tao and Zhang (2022) conduct a comprehensive analysis of 1,849 academic papers related to media exposure research published between 2000 and 2020. Meanwhile, the findings from Tao and Zhang (2022) indicate that media exposure research has demonstrated a general upward trend with periodic fluctuations, and that current and future research frontiers and hotspots focus on the effects of media exposure and its influencing factors.

The literature on media exposure can be categorized into three main areas based on the type of media: research on TV and film exposure, research on new media exposure, and comparative studies of exposure across different media platforms. First and foremost, the majority of studies on TV and film exposure focus on examining the consequences of such exposure. Barker et al. (2022) investigated the

portrayal of tobacco, alcohol, and foods high in fat, sugar, or salt in a sample of reality TV shows broadcast over a one-year period. The findings from Barker et al. (2022) indicate that exposure to imagery depicting these substances in media may promote their consumption among young people.

Focusing on the issue of violent movie exposure, which plays a critical role in driving the prevalence of violence, Eneizat et al. (2023) conclude that violent movie exposure has a direct impact on violent behaviour among Jordanian adolescents and that gender and socioeconomic status do not moderate the association between media exposure and violent behaviour in this population.

In addition, research on new media exposure constitutes the second major component of the literature. Though the investigation and comparison of digital users' motivations for news exposure, Rodríguez Virgili et al. (2022) discover that the majority of digital consumers favor unbiased news, meanwhile, it can be revealed that people's stated preferences for objective news increase with age. Moreover, those who are more interested in politics do like news that is reinforced, last but not lest, motivations for news exposure varies according on the nation under study.

Furthermore, comparative studies of exposure across different media platforms constitute the third component of media exposure research. Xu et al. (2020) contribute to the study on how residents' prospect ranks of disaster risk perceptions

are influenced by media exposure and disaster experience related to earthquake incidents. Xu et al. (2020) point out that, rural households mostly rely on TV broadcasts, in addition to mobile phones and online content from new media, to acquire information regarding disasters.

Additionally, according to Xu et al. (2020), there is a substantial negative correlation between the perceived severity of disaster prospects and exposure to traditional media. Moreover, Xu et al. (2020) assert that exposure to new media exhibits a significantly negative correlation with the perceived prospect ranks of the likelihood of disasters. Besides that, in accordance with Xu et al. (2020), the association between citizens' disaster experience and the perceived severity of disaster prospects is moderated by new media exposure.

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All of the above literature, including research on TV and film exposure, new media exposure, and comparative studies of different media exposures, indicates the growing prominence of media exposure research. However, with the evolution of video-sharing platforms and the rising popularity of web dramas, scholarly attention to web drama exposure remains limited. This gap in understanding hinders communication researchers from conducting comprehensive empirical analyses of web dramas. Consequently, incorporating web drama exposure as a mediating variable contributes to predictive modeling of audience satisfaction in Chinese web dramas.

2.2.6 Social Media Engagement

According to Hallock et al. (2019), social media engagement refers to the process through which individuals sustain relationships with other users and brands, extending beyond mere posting, liking, and commenting on social media platforms. Closer to communication research, Le (2018) considers social media engagement as individuals' online behaviors on social media platforms, including page viewing, clicking, content liking, sharing, and commenting.

In addition, Colicev et al. (2018) and Li et al. (2019) define social media engagement as active participation in which individuals voluntarily create, share, and consume specific content to express opinions or emotions through social media. Moreover, according to Oh et al. (2017) and Yoon et al. (2018), social media engagement denotes users' behavioral manifestations resulting from motivational drivers, including content consumption, participation in discussions, interaction with other individuals, and digital purchasing.

The definition proposed by Hallock et al. (2019) emphasizes the sustained relationships among social media users, yet fails to provide a communication-based perspective for elucidating such interactions. Meanwhile, the definition proposed by Le (2018) lacks in-depth elaboration. In contrast, the definitions from Colicev et al. (2018), Li et al. (2019), Oh et al. (2017), and Yoon et al. (2018) identify the forms of

social media participation and simultaneously emphasize that user behaviors on social media are active and driven by motivational factors; these definitions align with UGT and CCT and offer a more comprehensive conceptualization of social media engagement in the context of Chinese web dramas. Drawing on these definitions, this study defines web drama audience's social media engagement as active participation in which audience members voluntarily create, share, and consume web drama-related content through social media to express opinions or emotions, driven by motivational factors.

Through systematic review and classification, social media engagement research can be categorized into three main areas: social TV research, research on motivations for social media engagement, and research on impacts of social media engagement. In recent years, social TV research has received growing scholarly attention and is increasingly becoming a salient topic due to the evolution of social media. Aiming to explore how and why enjoyment is influenced by social TV viewing, Song et al. (2019) argue that the perceived similarity with virtual co-viewers positively enhances viewers' sense of social presence, thereby increasing enjoyment.

By examining how social TV viewers' motivations differ from those associated with traditional TV viewing and how viewers acquire content-related knowledge, Habes (2019) highlights the role of individual motivations in watching online social TV from the perspective of UGT, as well as social ability and usability factors. UGT is

instrumental in explaining motivations such as information seeking, learning, forming new social connections, maintaining daily routines, time management, escapism, entertainment, and relaxation (Habes, 2019). Moreover, social TV viewers' individual motivations are shaped by sociability and usability considerations (Habes, 2019).

According to Odunaiya et al. (2020), social TV, which refers to the integration of TV and social media, has significantly enhanced viewers connectivity and content engagement through social media interactions. They find that millions of individuals use social networking sites such as Facebook and Twitter to share their TV viewing experiences with others. Their findings indicate that social TV, regarded as a multi-screening and multitasking environment, enables viewers to follow their preferred shows, share TV-related content, transform TV viewing into online events, and interact with other viewers before, during, and after broadcasts. Furthermore, they highlight that social TV provides valuable insights for media industries and practitioners on leveraging social media effectively to attract larger audiences and support program promotion.

According to Tsai and Lin (2023), social TV research can be divided into four major domains: the design and interactive features of social TV, user motivations for engaging with social TV, content and usage patterns, and the media effects of social TV. Building on this research framework, Tsai and Lin (2023) identify a positive

correlation between TV program ratings and passive social media engagement, as well as between program ratings and the volume of official social media posts. However, their findings do not support a positive relationship between active social media engagement and program ratings (Tsai & Lin, 2023).

Regarding research on motivations for social media engagement, Suh et al. (2019) examine the relationships among motivation, satisfaction, and loyalty within social audiences of sports broadcasting. Their study highlights that sharing viewing experiences, information seeking, and enjoyment pursuit are key motivational factors significantly associated with viewing satisfaction in this context. In the meantime, Jarman et al. (2021) reveal that motives for social media use, such as information exchange, leisure, and escapism, are associated with social media engagement. Their findings also indicate mixed associations between social media use and body satisfaction as well as subjective well-being.

Regarding research on the impacts of social media engagement, Dubey and Sinha (2023) examine the relationship among social media exposure, anxiety, and panic buying, finding that social media exposure has a direct effect on panic buying. Meanwhile, anxiety partially mediates the association between media exposure and panic buying. These findings suggest that social media exposure contributes to increased anxiety among individuals. Barry et al. (2024) investigate the relationship between social media engagement and well-being among undergraduate

student-athletes, concluding that higher levels of social media engagement are associated with poorer well-being.

To sum up, in light of the growing popularity of social media, prior studies have focused on analyzing social media engagement from diverse perspectives, offering insightful and valuable references for communication researchers. In particular, as an emerging field, social TV research extends the application of social media engagement to TV viewing contexts and provides useful insights for the present study.

Although it is evident that an increasing number of web drama audiences share their viewing experiences and interact with other viewers on social media during and after the show, there remains a lack of research on social media engagement among web drama audiences (Mi et al., 2022; Su, 2022; Wang, 2022). This gap reflects the limited scholarly attention to the complementary roles of diverse new media from the perspective of CCT. Consequently, this study aims to investigate audience social media engagement, particularly its mediating effect, in order to develop a comprehensive predictive model of audience satisfaction in Chinese web dramas.

2.2.7 Social Media Community Size

Social media community represents a new context for the concept of community, shaped by the widespread success of social media (Papadopoulos et al., 2011).

According to Papadopoulos et al. (2011), social media community can be defined as a set of social media entities that share a common element of interest within a social media network, including explicit communities such as Facebook Groups and implicit communities presumed to exist within the system. Additionally, according to Cho and Wash (2021) and Naranjo-Zolotov et al. (2021), social media community is defined as a group of individuals who engage in sustained interactions with one another through the use of social media platforms. The two definitions mentioned above share certain similarities. However, the definition proposed by Papadopoulos et al. (2011) is more comprehensive, as it explicitly emphasizes that social media community is grounded in shared elements of interest. Therefore, this study defines a social media community as a set of social media entities that engage in sustained interactions with one another, centered on a common element of interest within a social media network.

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Moreover, Vellend (2010) defines community size as the total number of organisms in a community. In addition, Dolan (2015) proposes that the definition of social media community size is the number of active members within a given social media community. Building on the definitions proposed by Vellend (2010) and Dolan (2015), community size is defined as the total number of organisms in a community. Drawing on all the definitions above, the present study defines social media community size as the total number of social media entities that engage in sustained

interactions centered on a common element of interest within a group in a social media network.

Through a systematic review, it can be observed that the majority of studies on social media community size focus on analyzing the varying impacts of different community sizes, often treating community size as a moderator in the relationship between variables. They are reviewed as detailed below.

First, some studies have focused on examining how the effect of motivation on satisfaction is moderated by community size. Consistent with Yang et al. (2016), online community affiliation moderates the relationship between motivation and satisfaction. Moreover, Jiang et al. (2019) argue that the relationship between volunteering and life satisfaction is moderated by social network size; specifically, individuals who lost more friends experienced a greater increase in life satisfaction. Meanwhile, Liu and Pan (2020) find that friendship network size moderates the effect of linking social capital on life satisfaction among rural-to-urban migrants, with this relationship weakening as friendship network size increases. Furthermore, Zhang et al. (2022) demonstrate that the association between motivation and life satisfaction is strengthened by perceived social support. In addition, building on Morelli et al. (2023), the number of friends moderates the relationship between motivation and academic satisfaction, specifically reinforcing the negative association between these variables.

In addition, some studies argue that online community size moderates the association between media content and audience behavior. According to Dolan (2015), social media community size positively moderates the relationship between social media content and social media engagement behavior, based on empirical findings. Specifically, compared to entertaining content in small- or medium-sized social media communities, such content in large-sized communities has a stronger effect on social media engagement behavior. Meanwhile, Nepomuceno et al. (2020) find that social media content is not significantly associated with commercial performance in large online communities; however, online community size moderates this relationship in medium-sized communities.

The literature cited above highlights the significance of research on social media community size. Nevertheless, previous studies not only lack sufficient exploration of the moderating effect of social media community size, but also have not reached a consensus regarding whether this effect is positive or negative, thus warranting further investigation. Furthermore, the moderating role of social media community size has been rarely examined in the context of web drama research. Consequently, by employing social media community size as a moderating variable, this study aims to address this research gap through empirical testing of its moderating effect.

2.2.8 Media Effects

Media effects research constitutes a central focus of communication studies (Lowery & DeFleur, 1995). Perse and Lambe (2016) define media effects studies as research examining how the influence of mass media on individuals and society can be regulated, enhanced, or diminished. McQuail and Deuze (2020) describe media effects as the outcomes, whether intentional or not, of mass media activities. They further categorize these effects into cognitive, affective, and behavioral dimensions. Based on the above discussions, it is evident that audience satisfaction research forms a subset of media effects scholarship; therefore, a review of media effects literature is warranted.

Media effects research has a long-standing tradition in communication studies (Lowery & DeFleur, 1995; McQuail & Deuze, 2020; West & Turner, 2020). Prior to the new media era, media effects constituted a dominant area of inquiry, yielding numerous significant scholarly contributions. With the widespread adoption of new media technologies, research on media effects in digital and interactive environments has gained increasing prominence, opening new avenues for academic exploration. Accordingly, this study uses the emergence and diffusion of new media as a contextual boundary to divide media effects research into two distinct phases, facilitating a comprehensive review of the relevant literature.

2.2.8.1 Media Effects before the New Media Era

A substantial body of scholarly work has been dedicated exclusively to media effects over the past few decades. Lowery and DeFleur (1995) review 14 milestone studies in the field of mass media effects, including the research on the influence of film on children by Payne Fund studies in the 1920s, the study on the social panic caused by the broadcasting of *Invasion from Mars* in 1938, the survey of Erie County in 1940, the survey of the audience of daytime radio plays in the 1940s, Iowa hybrid seed corn diffusion adoption study, experiments on the persuasion effect of films during the Second World War, Yale Program of research on communication and persuasion, *personal influence* in 1955, Project Revere from 1951 to 1953, the research on the effect of TV on children by Schramm et al. from 1950s to 1960s, the study of the Agenda-setting Function since 1970s, the investigation on the relationship between the content of media violence and violence in daily life conducted by Gerbner et al. in the 1960s and 1970s, the large-scale study on TV and social behavior funded by the US Congress from the late 1960s to the early 1970s, the research on TV and behavior in 1982.

Moreover, according to Oliver et al. (2020), the historical development of media effects research can be divided into several distinct phases, the number and temporal boundaries of which vary across authors. However, the most frequently used classification identifies four periods: strong, weak, moderate, and negotiated effects. More specifically, the first phase of media effects history, spanning from World War

I to the late 1930s, is characterized by the belief that the public was highly susceptible to media influence (Esser, 2008). During this period, it was widely assumed that many, if not all, media outlets possessed nearly unlimited power to shape audience attitudes, routines, and behaviors (Oliver et al., 2020). Consequently, this era is commonly referred to as the "hypodermic needle" or "all-powerful media" effects phase (McQuail & Deuze, 2020).

In addition, the second phase of media effects history, spanning roughly from the late 1930s to the late 1960s, is characterized by the assumption that the media are largely ineffective in directly influencing audiences (Esser, 2008). Consequently, this phase is commonly referred to as the *weak effects* or *limited media power* period (McQuail & Deuze, 2020; Oliver et al., 2020). However, *limited media power* does not imply that the media have no effect whatsoever on audiences. More specifically, it refers to the absence of a direct and immediate link between media content and audience responses (Oliver et al., 2020).

Moreover, the third phase, spanning from the late 1960s to the late 1970s and commonly referred to as the moderate effects phase, was shaped by the rediscovery of significant media influences (Esser, 2008; Oliver et al., 2020). Prominent examples from this period include agenda-setting theory (McCombs & Shaw, 1972), cultivation theory (Gerbner & Gross, 1976), and the spiral of silence (Noelle-Neumann, 1974).

Furthermore, beginning in the late 1970s, the fourth and final phase of media effects research has been ongoing. Since then, scholars have increasingly adopted terms such as negotiated effects, transactional media effects, or complex reciprocal media effects to describe the dynamic nature of audience-media interactions (McQuail & Deuze, 2020; Oliver et al., 2020). It should be noted that, as McQuail and Deuze (2020) emphasize, the four-phase model represents only one interpretive framework and is best understood as a synthesis of diverse perspectives rather than a linear historical trajectory of research and scholarship.

2.2.8.2 Media Effects in the New Media Era

With the widespread adoption of new media, media effects research on new platforms has gained significant attention. Numerous studies apply classical communication theories to investigate media effects in new media contexts, opening up promising avenues for scholarly inquiry. Zhou and Zhao (2021) employ big data analytics to examine the evaluation of audio-visual content effects in the era of media convergence through the framework of Media System Dependency Theory.

The key contributions of Zhou and Zhao's (2021) research include the development of an indicator system for evaluating audio-visual content effects and an investigation into how various indicators influence audience ratings. In addition,

Zhou and Zhao (2021) assess the dissemination effectiveness of different TV dramas, arguing that audiences are more dependent on dominant communication platforms.

Moreover, Yang and Tian (2021) examine the third-person effect of fake news in the context of the COVID-19 pandemic and find that social media engagement directly strengthens this effect, while self-efficacy and perceived knowledge contribute to its indirect reinforcement. Tang et al. (2021) develop a research model based on Cultivation Theory and Protection Motivation Theory to investigate how exposure to government social media content cultivates individuals' information security behaviors during the COVID-19 crisis, highlighting the critical role of government social media in crisis-related information security management. Danner et al. (2022) explore agenda-setting effects by analyzing the association between topics covered in news articles and audience comments posted on news websites. Their findings demonstrate that issues emphasized in news articles are also perceived as important in reader comments, but the reverse influence is not observed.

As a central component of communication research, media effects scholarship has attracted extensive scholarly attention. The studies reviewed above demonstrate that media effects research is rich, diverse, and impactful, particularly highlighting 14 landmark studies in the field of mass media effects, which are widely regarded as foundational and influential. Nevertheless, two limitations can be identified in this

body of work. First, the generalizability of the findings remains uncertain, as it has yet to be fully established whether these conclusions apply to developing countries.

In addition, the crisis of theoretical stagnation in media effects research continues to challenge communication scholars. In response to this pressing issue, researchers argue that empirical communication research has gradually become rigid and lacks innovative insights (Maigret & Fang, 2009). This is not due to a lack of meaningful contributions, but rather because the field has exhausted its own conceptual and methodological logic.

Given these challenges, there is a need to identify new breakthroughs in media effects research. In response to the two issues outlined above, this study conducts media effects research on Chinese web drama audiences from the perspectives of UGT and CCT, both of which are well-established and influential theoretical frameworks that emphasize audience agency. At the same time, a big data analytics approach is employed to enhance the potential for advancing current media effects scholarship.

2.2.9 Social Media Big Data Analytics Approach

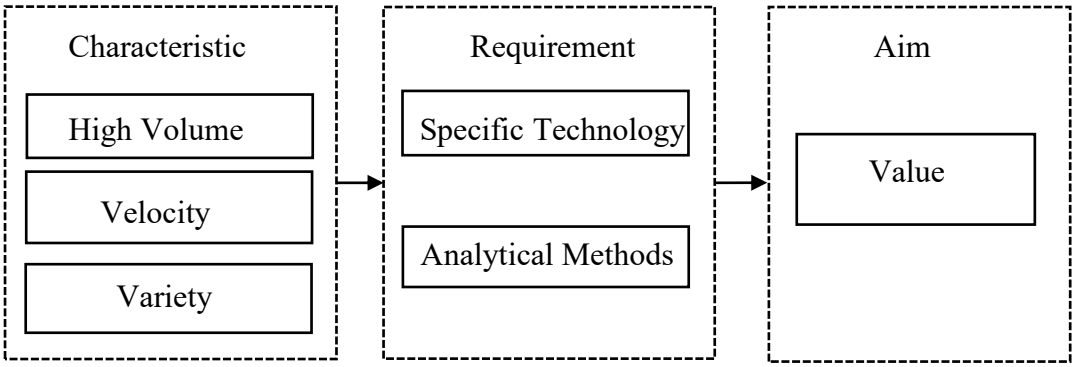
2.2.9.1 Definition of Big Data

Big data refers to the adoption of all data, it is no longer a random sample, the prediction is the core of big data (Mayer-Schönberger & Cukier, 2013). Additionally,

Hair et al. (2019b) propose that, big data is defined as the secondary data explosion that is signified by a surge in the volume, variety, and velocity of data accessible from diverse sources, including social media. Moreover, from the perspective of research method, Babbie (2020) makes the assertion that big data is defined as the enormous datasets which are automatically generated from online activities.

Moreover, Castellani and Rajaram (2021) supply the characteristic of big data, covering volume, variety, velocity, variability, veracity, vulnerability. Besides that, Clark et al. (2022) offer the definition of big data from the perspective of research method, that is, big data is considered as extraordinarily massive data sources, too big to handle and analyze with traditional techniques. Meanwhile, big data can be utilized to describe other types of advanced data analytics, such as predictive analytics, in addition to the size of the data source (Clark et al., 2022).

In addition, a more precise definition of big data is provided by De Mauro et al. (2015). According to these authors, big data refers to information assets characterized by high volume, velocity, and variety, which require specific technologies and analytical methods to be transformed into value. This definition is illustrated in Figure 2.1 below.



Source: De Mauro et al. (2015)

Figure 2.1 The Illustration of Big Data Definition

In Figure 2.1 above, high volume, velocity and variety are regarded as the characteristics of big data, and the specific technology and analytical methods are considered as the requirement of big data, while the value is characterized as the aim of big data (De Mauro et al., 2015). As the the information assets, big data with the characteristics of high volume, velocity and variety can be converted into the value relying on the specific technology and analytical methods (De Mauro et al., 2015). This investigation embraces this definition of big data due to that it is more precise.

2.2.9.2 Social Media Big Data Analysis

Carr and Hayes (2015) define social media as online platforms that are widely used as permanent means of mass-personal communication, primarily delivering value through user-generated content and enabling users to interact with one another. Moreover, Kapoor et al. (2017) assert that social media is a collection of user-driven digital platforms providing an environment that fosters networking and interactions at multiple levels, facilitating the sharing of engaging content, initiating dialogues,

and expanding one's social network. In view of the focus on diverse user-driven platforms that facilitate the diffusion of compelling content and the high concentration of user-generated content on social media platforms, this study adopts the definition proposed by Kapoor et al. (2017).

Using examples and case studies, Finger and Dutta (2014) demonstrate how to extract considerable economic value from big data through the Ask-Measure-Learn framework, a system designed to help individuals assess relevant content and data, ask appropriate questions, and derive knowledge from their findings to realize the potential of big data. Meanwhile, Finger and Dutta (2014) illustrate how social media analytics can be specifically applied to public relations, marketing, sales, and customer service.

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In addition, Ghani et al. (2019) summarize current research to provide a comprehensive understanding of social media big data analytics by comparing diverse big data analytics approaches and their characteristics, and by discussing the application of social media big data analysis through highlighting innovative methodologies, techniques, and quality dimensions across various studies. More specifically, Ghani et al. (2019) propose a four-part classification of social media big data analysis. This classification includes data sources, traits, computational intelligence, and approaches, enabling researchers to systematically understand the tools and methods used in analyzing social media big data.

In addition, McQuail and Deuze (2020) emphasize that it becomes considerably more difficult to determine when and how individuals form into audiences. As a result, media industries are compelled to seek more comprehensive audience data, such as big data. Although big data technology capable of efficiently crawling large-scale datasets has been applied in communication research for several years, there is still ongoing debate regarding the methodological classification of big data analytics (Zhao & Wu, 2020).

Moreover, in China, Zhou and Zhao (2021) apply big data analysis to evaluate the media effects of audio-visual content in the era of media convergence by examining social media applications. Their study inspires communication researchers to leverage big data technology to explore audience motivations, emotions, and behaviors. According to Zhou and Zhao (2021), the application of big data analytics in communication research falls into two categories. The first involves researchers using web crawling technology to collect large-scale data from the Internet, which is then processed through sentiment analysis and transformed into structured data suitable for statistical analysis. The second entails direct access to pre-processed structured data generated through advanced big data computation enabled by platform-specific technologies. This approach benefits from data sharing by major Internet companies that possess strong capabilities in big data processing and analytics.

Furthermore, Abkenar et al. (2021) demonstrate how social media and big data analytics interact by providing an extensive overview of big data analytic techniques used in social networks, based on a review of published papers from 2013 to 2020 that identified 74 relevant publications. As Abkenar et al. (2021) state, big data analysis methodologies are divided into two types: network-oriented and content-oriented approaches.

Meanwhile, Babbie (2020) provides a detailed introduction to the social media big data approach. First and foremost, Babbie (2020) elaborates on the integration of big data analytics with social media, noting that while big data is widely used by commercial companies such as Google and Amazon, platforms like Facebook and Twitter serve as significant sources of such data. In addition, social media big data analysis is regarded as an emerging methodology that opens new avenues for social research and is increasingly addressed in social research journals (Babbie, 2020). In sum, the application of social media big data can assist researchers in generating more original insights and inspiration in the new media era, making it highly dynamic and promising within the field of social research (Babbie, 2020).

In addition, Clark et al. (2022), who are engaged in research on social research methods, state that big data is a fascinating source of material for social scientists because it is not generated for research purposes. They further note that social media

platforms such as Facebook, Twitter, and Instagram have become the primary sources of big data used in social research; in other words, social scientists primarily focus on social media big data.

2.2.9.3 Social Media Big Data Prediction

There are quite a few studies on social media big data prediction. As Mayer-Schönberger and Cukier (2013) note, the core of big data lies in prediction. Additionally, Finger and Dutta (2014) emphasize the significance of prediction through social media big data, pointing out that the common goal of all social media applications and their data analysis methods is to develop the ability to predict future outcomes. They illustrate this with the example of the film industry, linking entertainment program prediction research to social media big data analysis. Furthermore, Finger and Dutta (2014) argue that using social media for movie box office prediction is feasible and that related analytical approaches should be further advanced.

At the same time, Hair et al. (2019b) highlight the significance of big data and big data analysis, arguing that the types and scope of analyses have been revolutionized by the big data analytics approach. They further reveal that big data analytics focuses on social media and network analysis, and that predictive research has been identified as one of five types of big data analysis based on analytical objectives in

recent studies. This assertion encourages communication researchers to engage in predictive research through the social media big data analytics approach.

Adopting a sample of 127,629 reviews, Zhao et al. (2019) predict overall customer satisfaction based on customers' social media reviews and find that longer text reviews with higher levels of subjectivity and readability are associated with lower levels of overall customer satisfaction. At the same time, Zhao et al. (2019) reveal that greater consumer involvement in writing reviews has a positive effect on their overall satisfaction.

Moreover, Simon and Schroeder (2020) employ social media big data analytics to forecast film popularity and assess viewer interest. They point out that the box office performance of Hollywood blockbusters can be effectively predicted using big data. Building on social media data from platforms such as Facebook, YouTube, Twitter, and Instagram, Chaudhary et al. (2021) develop a social media consumer behavior model using machine learning to predict customer behavior through big data analytics.

Furthermore, Mi et al. (2022) aim to predict web drama views using sentiment analysis and an improved stacking ensemble model. They find that the improved stacking ensemble model can further enhance predictive performance. Meanwhile,

Mi et al. (2022) point out that video view forecasting can assist web drama creators and investors in adjusting their marketing and investment strategies.

In addition, Liu et al. (2022) employ machine learning techniques with big data derived from viewer behavior, consisting of over 16,000 real-time messages and more than 5,500 virtual gifts. Specifically, they investigate how audience value perception affects gift-giving behavior, with satisfaction serving as a mediating variable. Based on their analysis, Liu et al. (2022) find that satisfaction fully mediates the effect of audience value perception on gifting amount and partially mediates its effect on gifting frequency.

2.2.9.4 Sentiment Analysis Application in Communication Research

The representative study on applying sentiment analysis to social media big data analysis is conducted by Tao et al. (2019), who employed the web crawler software GooSeeker to collect 27,500 traveler comments from Sina Weibo (now known as Weibo) between January 2011 and December 2017 regarding air quality at 195 tourist attractions in China. Their analysis reveals that visitors generally hold positive perceptions of air quality and exhibit limited awareness of air pollution risks.

Liu (2020) provides a definition of sentiment analysis, which is also known as opinion mining and is defined as the computational study of people's emotions, moods, sentiments, opinions, and attitudes expressed in written text. According to

Liu (2020), sentiment analysis research encompasses several areas, including sentiment classification, comparative opinion analysis, opinion summarization and retrieval, debate and comment analysis, intention mining, and fake opinion detection. Sentiment analysis has become a compelling, active, and challenging research domain within natural language processing (NLP), a key area of computer science and artificial intelligence (Liu, 2020).

As Liu (2020) notes, sentiment analysis, which originated in computer science, has expanded into the social sciences due to its growing significance in commerce and society in recent years, and communication research is no exception. According to Liu (2020), the rapid development of sentiment analysis has kept pace with the growth of social media on the web. Furthermore, Liu (2020) explains that a large volume of social media data has been digitally recorded on a large scale, marking the first time in human history that opinion-rich data have become widely available, which makes it increasingly attractive for academics to mine these data and extract valuable insights through sentiment analysis. In addition, Liu (2020) provides researchers with numerous examples of how sentiment analysis has been applied in practical contexts, such as predicting movie success and box-office revenue.

In recent years, sentiment analysis has been widely adopted in empirical studies. Focusing on the use of sentiment analysis to identify trending patterns in YouTube video games, Gajanayake and Sandanayake (2020) offer recommendations regarding

key characteristics of YouTube videos, including publication time, title length, view counts, and likes. In analyzing comments from over 150 web dramas, Mi et al. (2022) employ lexicon-based sentiment analysis, a method widely adopted due to its simplicity, to forecast web drama viewership. The study further indicates that an improved stacking ensemble model can enhance predictive performance beyond what is achieved through sentiment analysis alone.

Moreover, by integrating machine learning–based sentiment and topic analysis with NLP applied to large-scale tweet data, Chang et al. (2022) investigate public sentiments and prevalent topics related to COVID-19 vaccines. Their findings reveal that concerns about the vaccines increased during the rollout and implementation of vaccination programs, yet positive sentiments and emotions ultimately outweighed negative ones overall.

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Furthermore, Wankhade et al. (2022) argue that technological advancements such as big data, blockchain, and cloud computing have significantly expanded the applicability of sentiment analysis, enabling its deployment across virtually any domain. Meanwhile, they emphasize its widespread adoption in the media industry, where audience responses can be assessed through the analysis of comments on drama series and movies. This not only helps audiences make more informed viewing decisions but also promotes the dissemination of high-quality content (Wankhade et al., 2022).

In the meantime, aiming to examine the significant impact of big data analysis on client relationship management, Ijomah et al. (2024) leverage sentiment analysis to gain valuable insights into clients' attitudes and perceptions. This approach helps organizations improve their strategies and address customer dissatisfaction (Ijomah et al., 2024). Furthermore, through a comprehensive review of sentiment analysis, Sharma et al. (2024) highlight its key characteristics, applications, value, significance, and challenges, while also examining the suitability of existing datasets and deep learning technologies for sentiment analysis.

In brief, sentiment analysis has emerged as an active, engaging, and promising research domain in recent years. It serves as an effective method for social media big data analytics in communication studies, facilitating the discovery of valuable information and the generation of novel insights in the Internet era. A review of the literature on social media big data analytics enables communication researchers to access numerous references and conceptual inspirations for effectively implementing predictive modeling and sentiment analysis. For instance, the application of the web crawler tool GooSeeker by Tao et al. (2019) offers methodological guidance for this study, while the detailed discussion of intention mining and the proposed procedural approach to conducting such analysis by Liu (2020) provides a clear directional framework for the present research.

However, most of the previous studies are not closely integrated with communication studies. This suggests that communication researchers have not done enough to leverage big data and sentiment analysis in advancing communication research. Moreover, communication investigations employing the social media big data analytics approach often lack support from foundational communication theories and comprehensive conceptual models, and the resulting lack of research depth limits the generation of new scholarly contributions in communication research. As a result, this study adopts UGT and CCT as the theoretical foundations to support the development of a predictive model using the social media big data analytics approach.

2.2.10 The Theoretical Framework of the Study

To conduct the predictive modeling of audience satisfaction in Chinese web dramas, this study employs UGT and CCT as its theoretical framework. The integration of the two theories provides a solid foundation for the conceptual model of this study, thereby enabling predictive modeling.

2.2.10.1 The Uses and Gratifications Theory (UGT)

UGT clearly posits that audiences use the media to fulfill their diverse needs and interests (McQuail & Deuze, 2020; West & Turner, 2020). It emphasizes the motivations and purposes underlying audience media use and encourages researchers to focus on investigating audience needs (McQuail & Deuze, 2020; West & Turner,

2020). From the perspective of UGT, the demands of media users are of central importance (Kasirye, 2022). From traditional media research to new media research, UGT has remained a widely used theoretical framework among scholars (McQuail & Deuze, 2020; West & Turner, 2020).

As a stable and mature theory, UGT was proposed by Katz, Blumler, and Gurevitch (1974). It is defined as follows: media users actively select media and messages with specific motives; moreover, the active selection and use of media and messages aim to fulfill audiences' social and psychological needs (Katz, 1959; Katz et al., 1974). According to McQuail and Deuze (2020) and West and Turner (2020), the uses and gratifications process is described as follows: social and psychological origins of needs give rise to expectations of the mass media or other sources, leading to differential exposure (or engagement in other activities), which in turn results in need gratification and other outcomes.

In recent years, the UGT is applied to study new media especially the social media. Gan and Li (2018) aim to investigate the effect of various gratifications on the continuance intent of WeChat usage in China. Gan and Li (2018) consider that the motivations of choosing and using media are perceived enjoyment, leisure, social presence, self-presentation, social engagement, documentation, information exchange, and media attraction. Bucknell and Kottasz (2020) explore the uses and gratifications pursued by the principal target market of a novel social media platform,

claiming that the gratification of entertainment/affect is the principal motivator for all behaviors.

In addition, Kim et al. (2021b) announce that the gratification factors of social media content greatly impact on participants' intent to disseminate information, perceived information trust, and thus their intention to participate in the event. Meanwhile, Kim et al. (2021b) make the assertion that non-contents operates as crucial moderators, affecting the impacts of gratification factors on participants' intent to disseminate information and perceived information trust. Besides that, the finding from Wang (2021) reveals that social media utilization is positively correlated with both kinds of gratifications among Chinese temporary migrants from the viewpoint of UGT.

Moreover, Thongmak (2021) validates the influence of Internet atmosphere gratifications and information seeking on the intent to search online from UGT perspective, it is verified that the search performance is affected by intent to online search and behavior of online search. Meanwhile, Yücel and Çapraz (2022) reveal that, there are five uses and gratifications of Turkish female audience for viewing Indian soaps, comprising identity, pleasurable guilt, leisure and escape, moral reinforcement and idealization. In the meantime, the audience leverage viewing of Indian soaps to voice their disapproval of Turkish serials (Yücel & Çapraz, 2022).

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Building on UGT, Abdul Hamid et al. (2022) point out that the housewives' motivations for utilizing social media positively influences both flourishing and well-being, in the meantime, five themes are obtained from the thematic analysis by them. In the meantime, Zhang et al. (2022) examine the factors influencing college students' mobile learning continuance from the perspective of UGT, their findings indicate that perceived integration has a direct and indirect impact on mobile learning continuance through students' gratifications. Han et al. (2023b) integrate the UGT with technology acceptance model to establish a comprehensive conceptual model for analyzing the motivational factors influencing contemporary Chinese college students to utilize social media for viewing the news.

Besides that, many investigators adopt UGT to undertake the web video research in recent days. Golob et al. (2021) employ the UGT approach in the context of YouTube gameplay video watching, they point out that the attractiveness of the player is the most important motivation. In addition, Golob et al. (2021) announce that some motives might be triggered by the technological characteristics of the medium itself. In the meantime, Yang and Ha (2021) investigate the motivation of using Chinese TikTok among young consumers from UGT viewpoint, discovering that the entertainment gratification is the primary motivation in using Chinese Tiktok.

In addition, relying on UGT, Lin (2022) asserts that the degree to which users enjoy self-documentation, amusement, passing the time, and self-expression on Instagram is closely associated with their stickiness, which plays a significant role as a mediator in the development of compulsive Instagram usage. Customers' mindfulness can both reduce and moderate the impact of stickiness on compulsive Instagram usage (Lin, 2022). Besides that, Menon, D. (2022) argues that subscription intent of over-the-top video streaming platforms is forecast by convenient navigability, binge watching, and relaxation. Meanwhile, Menon, D. (2022) makes the statement that continuing intent of it is predicted by convenient navigability, binge watching, and entertainment based on UGT.

Concentrating on the psychological and behavioral aspects of reality program fans, Gong and Huang (2022) reveal that viewing motives, social interaction, voyeurism, and suspense exert a significant and positive influence on web fan engagement within the framework of UGT. From a UGT perspective, Zhu et al. (2024) indicate that the use of short videos on social media is directly associated with youth depression, and this relationship is mediated by need gratification and short video addiction.

On the basis of UGT, Lu and Chen (2024) are devoted to the investigation of audience' participation in and satisfaction with various forms of *danmu* (refers to the real-time comments synced with a certain play time and location throughout the web

video), pointing out that additional cultural information *Danmu* emerges as the most rewarding form, profoundly fulfilling audience' demands for information and amusement.

Additionally, Chapman and Abraham (2024) employ UGT to explore the impact of audience's psychological aspects on their motives for viewing web audio-visual media, making the conclusion that all forms of media engagement are rooted in the human desire for affect. Syafira and Dharmmesta (2024) aim to research the antecedents and consequences of subscribing to video streaming services, they claim that subscribers of video streaming services prioritize service usability, content diversity, amusement, and leisure. On top of that, the investigation from Alhabash et al. (2024) demonstrates the distinctions in the uses and gratifications of four prominent social media platforms, including Facebook, Instagram, Twitter, and TikTok, making the argument that Instagram possesses the excellence among these social media.

These studies obtain the accomplishments of explanation and application of UGT and greatly enrich this important communication theory, which should be taken in and learned. However, those research on the Chinese media industry from UGT perspective still lags behind industry evolution (Gong & Huang, 2022). Concerning this investigation, there are limited studies using UGT in the field of Chinese web drama research.

When commenting on UGT, McQuail and Deuze (2020) emphasize that it is becoming extremely harder to find a single explanatory framework that adequately explains audience patterns due to the diversification of the media environment from UGT perspective. Given that, this study combines the research on audience satisfaction of Chinese web drama with UGT by means of big data analytics approach, that is good for keeping pace with the development of Chinese web drama industry, being of great use in achieving the breakthrough of UGT in the age of new media.

2.2.10.2 Channel Complementarity Theory (CCT)

CCT, proposed by Dutta-Bergman (2004a), suggests that individuals who consume one medium to obtain information in a particular area are likely to use other media that provide information in that same field. According to Dutta-Bergman (2004a), CCT originally refers to the integration of conventional and online media consumption within a certain content domain, it claims that consumers of online news in a certain topic area are also more likely to look for news in the same area from conventional media sources. In other words, older information channels are not simply replaced by new ones, on the contrary, they coexist in tandem to enrich audiences' information-seeking habits (Dutta-Bergman, 2004a).

Shortly afterward, Dutta-Bergman (2004b) enriches CCT and contends that people who use one type of media to meet a specific functional need also utilize other types of media to meet that need. For instance, those who had telephone conversations with friends and relatives regarding the 9/11 attacks were also more likely to have online conversations with them (Dutta-Bergman, 2004b). Soon, Dutta-Bergman (2006) provides evidence in favor of the notion of channel complementarity, arguing that people who engaged in online forums to discuss the attacks and exchange ideas with others were also more likely to do so in offline groups.

In recently years, CCT is extended to many different domains of communication. Glynn and Huge (2014) apply CCT to investigate the selections and combinations of communication channels that people utilize to obtain economic information, with a particular focus on the distinctions between offline and online economic communication. The findings from Glynn and Huge (2014) showcase a high degree of complementarity between traditional and new media, face-to-face conversation, and professional communication as various forms of economic communication. Bobkowski et al. (2018) extends the precepts of CCT into the domain of online news sharing, and advances our knowledge of news readers who distribute hyperlocal content via social media, email, and in-person interactions. Therefore, the investigation from Bobkowski et al. (2018) adds to the body of knowledge on online news sharing, word-of-mouth, and hyperlocal news.

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Moreover, the findings from Neyazi et al. (2019) demonstrate that exposure to social media is significantly predicted by exposure to traditional media. Sharing text messaging, in-person discussions, radio listening, and campaign interest all anticipate the sharing of information on social media (Neyazi et al., 2019). There is a favorable relationship between exposure to conventional and new media and information-sharing, it offers valuable insights into CCT (Neyazi et al., 2019).

Additionally, Zhang et al. (2020) extend CCT to the research of health information acquisition, confirming the existence of media complementary between information-oriented media (such as newspaper and magazine) and entertainment-oriented media (such as TV). Meanwhile, the discoveries from Zhang et al. (2020) present the complexity of media complementary, particularly in the digital age.

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Furthermore, building on CCT, Liao et al. (2021) point out that brand community-swinging of customers is influenced positively by the complementarity of gratification in three values, including value of information, value of social interactions, and value of one's appearance, which strengthens brand loyalty. Besides that, Jiang and Liu (2022) investigate the patterns of media complementarity for health information seeking in India on the basis of CCT, demonstrating that media complementarity exists between these two categories of media rather than within print media (such as newspapers, books, and magazines) or broadcast media (such as

radio and TV). Additionally, there is the complimentary relationship between print and broadcast media and the Internet (Jiang & Liu, 2022).

Meanwhile, focusing on the integrated effect and complementarity systems of live streaming and customer web comments on purchasing intent, Qin et al. (2023) embrace CCT to establish an influence model of twin channels, making the argument that customer's purchasing intent is affected by both live streaming and customer web comments, and customer engagement serves as a mediator. The investigation from Qin et al. (2023) supplies innovative insight into the complementarity of differential new media.

On top of that, Wang et al. (2024) combine CCT and UGT to accomplish the investigation on the issue of social media platform-switching, shedding light on the driving force of social media platform-switching behavior, namely supplemental and complementary demands of individuals. In addition, Wang et al. (2024) point out that various social media platform-switching behaviors possess diverse preferences for media affordance based on the supplemental and complementary demands.

As a prominent theory, CCT enables communication researchers to access novel perspectives on media research and audience analysis. However, a notable limitation in existing studies should be acknowledged: most CCT-related research focuses primarily on the complementarity between new media and traditional media,

overlooking the complementarity among different new media platforms. In contrast, it is precisely this inter-new-media complementarity that more accurately reflects the evolving media landscape of the digital age. Building on CCT, this study incorporates the complementarity of diverse new media into the investigation of audience satisfaction in Chinese web dramas, thereby advancing theoretical application and contributing to scholarly innovation.

2.2.10.3 Integration of UGT and CCT

First, there exist notable commonalities between UGT and CCT, underscoring the theoretical compatibility and feasibility of integrating the two frameworks. To be specific, both theories focus on media usage behavior (McQuail & Deuze, 2020; Qin et al., 2023; Wang et al., 2024). Moreover, both theories emphasize the active role individuals play in selecting and engaging with media, highlighting their agency in the media consumption process (Liao et al., 2021; McQuail & Deuze, 2020). Furthermore, both theories highlight that media usage behavior is oriented toward the fulfillment of individuals' needs (Dutta-Bergman, 2004b; McQuail & Deuze, 2020).

In addition, a complementary relationship is evident between UGT and CCT, thereby highlighting the imperative of integrating these two theoretical frameworks. According to West and Turner (2020), UGT provides a robust framework for understanding why individuals use the media. Meanwhile, CCT emphasizes how audiences engage with diverse media (Jiang & Liu, 2022; Qin et al., 2023; Wang et

al., 2024). These two theories complement each other to enable a more profound and comprehensive analysis of the issues at hand. Given the strong theoretical alignment and complementarity between the two theories, their integration is well justified.

On top of that, recent scholarly efforts have integrated UGT with CCT. Liao et al. (2021) integrate UGT and CCT to investigate the antecedents and outcomes of brand community-swinging. Building on the integrated theoretical frameworks of UGT and CCT, Wang et al. (2024) argue that platform-swinging behavior arises from users' needs for complementarity and supplementation across digital platforms. These empirical studies indicate that integrating UGT and CCT can enhance the explanatory and exploratory power of these frameworks in media research.

The integration of the two theories establishes a robust foundation for constructing the research framework of this study, thereby facilitating predictive modeling. At first, given that both theories highlight that media usage behavior is oriented toward the fulfillment of the audience's needs (Dutta-Bergman, 2004b; McQuail & Deuze, 2020), the combination of the two theories provides well-grounded support for the research framework on audience satisfaction. Meanwhile, audiences actively select and engage with media, a point highlighted by both theories (Liao et al., 2021; McQuail & Deuze, 2020). Therefore, the variable of web drama viewing motivation can be incorporated into the research framework to establish its relationships with other constructs. Furthermore, given that both theories focus on media usage

behavior, integrating them can effectively incorporate the variables of web drama exposure, audience social media engagement, and social media community size into the research framework, thereby establishing their relationships with other constructs. In summary, the integration of UGT and CCT enables the construction of a more profound and comprehensive research framework, thereby providing a robust foundation for predictive modeling of audience satisfaction in Chinese web dramas within this study.

2.2.11 The Conceptual Model of the Study

Based on UGT, CCT, and relevant studies, the conceptual model of this study can be accurately formulated. Specifically, the model comprises five constructs: web drama viewing motivation as the independent variable, web drama audience satisfaction as the dependent variable, web drama exposure and audience social media engagement as mediating variables, and social media community size as the moderating variable. Among these constructs, web drama exposure and audience social media engagement serve as sequential mediators, forming a chained mediation mechanism (Chen et al., 2021; Ding & Wang, 2022; Hayes, 2009; Zhu et al., 2021). All variables in this study are continuous. The framework is illustrated in Figure 2.2 below.

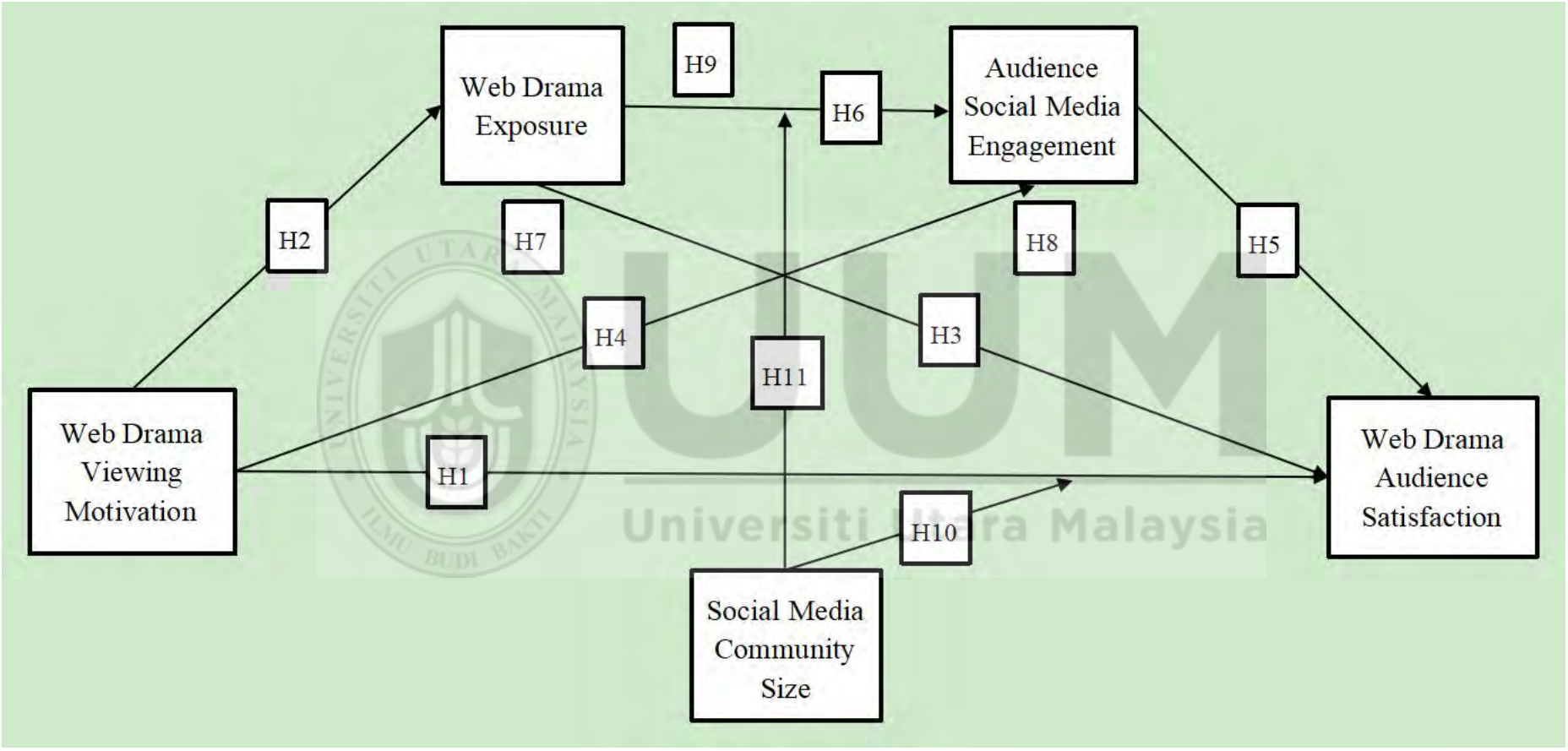


Figure 2.2 The Conceptual Model of the Study

This conceptual model illustrates the eleven hypothesized relationships among the five constructs. Specifically, H1 through H6 represent direct relationships; H7, H8, and H9 denote mediating relationships, with H9 specifically indicating a chain-mediation effect (Chen et al., 2021; Ding & Wang, 2022; Hayes, 2009; Zhu et al., 2021). In addition, H10 and H11 represent moderating associations.

Furthermore, because the multiple-step multiple mediation process is moderated by a moderating variable in this model, it is designated as a moderated multi-step multiple mediation model (Hayes, 2009; Huang et al., 2024; Liu et al., 2024; Rialti et al., 2019; Xu et al., 2024; Zhang & Wei, 2024). This model offers a novel, prominent, and promising framework for predictive modeling of audience satisfaction in Chinese web dramas.

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2.2.12 Development of Research Hypotheses

Based on these foundational theories and prior relevant studies, this section proposes the research hypotheses of the study, which include hypotheses concerning direct effects, mediating effects, and moderating effects.

2.2.12.1 Research Hypotheses of Direct Effects

According to UGT, media users actively select media and messages based on specific motives (Katz, 1959; Katz et al., 1974). The theory posits that social and psychological needs generate expectations of mass media or other information

sources (McQuail & Deuze, 2020; Katz et al., 1974; West & Turner, 2020). This leads to selective exposure or engagement in alternative activities, which ultimately results in need gratification and various outcomes. In addition, as stated by Hu (2021) and Wang (2022), the primary motivations for viewing web dramas include entertainment, relaxation, escapism, passing time, information seeking, and social interaction. Therefore, building on UGT, it can be inferred that web drama audience satisfaction may be influenced by web drama viewing motivation.

Related studies yield similar results. Suh et al. (2019) found that audience satisfaction in social viewing contexts is positively influenced by viewers' motivations, such as sharing viewing experiences, information seeking, and entertainment seeking. Furthermore, Tefertiller and Sheehan (2019) identified five motivators for watching TV, with the need for relaxing entertainment being the strongest predictor of audience satisfaction.

Additionally, Kang and Cho (2020) identified five motivators for engaging with video content: self-evaluation and development, leisure and sensory stimulation, amusement, time passing, escapism, and trend-following. Each of these factors influences viewing satisfaction differently. Meanwhile, Pappas et al. (2020) demonstrate that users' motivations play a significant role in determining their satisfaction with social networking sites, and that such satisfaction can be explained and predicted by these motivations. Furthermore, Liu et al. (2022) argue that

audience satisfaction on the viewing experience is influenced by audience value perception; moreover, audience value perception, regarded as a stimulus, is equivalent to audience viewing motivation. Therefore, it can be inferred that viewing motivation affects audience satisfaction.

Drawing on UGT, Periaiya and Nandukrishna (2023) contend that motivations such as entertainment, modality, navigability, and escape positively influence affective media satisfaction on over-the-top video streaming platforms. These platforms serve as dissemination channels for web premium video content. Additionally, Jin et al. (2023) argue that specific motivations such as cognitive needs, affective needs, personal integrative needs, and social integrative needs positively influence Malaysian university students' satisfaction with Instagram use. These motivations are rooted in the functional roles that social media fulfill for individuals.

Meanwhile, studies by Suh et al. (2019), Tefertiller and Sheehan (2019), Kang and Cho (2020), Gong and Huang (2022), and Periaiya and Nandukrishna (2023) indicate that entertainment seeking, relaxation, time passing, information seeking, and escapism serve as viewing motivations in the context of audio-visual program consumption. These findings align with and are extended by the conclusions of Hu (2021) and Wang (2022), who argue that, as a new form of audio-visual content, web dramas serve to fulfill audience needs for entertainment, relaxation, escapism, passing time, information seeking, and social interaction. Accordingly, the studies

reviewed above indicate that viewing motivation has a direct effect on audience satisfaction. Building on this body of research, the present study proposes the first hypothesis as follows:

Hypothesis 1: Web drama viewing motivation affects web drama audience satisfaction.

Building on UGT, the social and psychological origins of needs that give rise to expectations toward mass media or alternative sources lead to differential media exposure (McQuail & Deuze, 2020; Katz et al., 1974; West & Turner, 2020). This variation in exposure, or engagement in other activities, ultimately results in need gratification and associated outcomes. Given that the social and psychological origins of needs lead to differential media exposure, it could be inferred that audience motivation influences media exposure.

In psychological research, motivation is defined as the driving force underlying the initiation, persistence, direction, and intensity of goal-directed behavior (Colman, 2015; Zhang, 2019). Therefore, based on this definition, a clear direct relationship may exist between motivation and behavior, such that specific levels of motivation may lead to corresponding behavioral outcomes. In conclusion, it can be inferred that web drama exposure is influenced by viewing motivation.

Similar findings have been reported in related communication studies. Lin et al. (2018) indicate that the positive relationship between the social-infotainment motive and social TV participation suggests viewers engage in social TV activities more frequently and invest more time in them when motivated by social, entertainment, and information-related gratifications.

The findings from Lin et al. (2018) indicate that audience motivation positively influences media exposure. Moreover, their results enhance understanding of the predictive capacity of social TV usage motivations and support the use of motivation in predicting behavioral outcomes.

Additionally, the results from Tefertiller and Sheehan (2019) show that three motivations are identified for TV viewing: relaxing entertainment, information seeking, and social interaction. These motivations reflect distinct user needs in the context of TV consumption. Building on the findings of Tefertiller and Sheehan (2019), it could be observed that these motivations are associated with TV viewing, which constitutes a form of media exposure.

Moreover, the findings from Kim and Kim (2020a) demonstrate that viewing motivation for a travel reality show positively influences presence, which is regarded as a viewing experience that is analogous to web drama exposure to some extent.

Therefore, it can be inferred from Kim and Kim (2020a) that media exposure is affected by viewing motivation.

In addition, focusing on binge-watchers, Castro et al. (2021) investigate how viewers' motivations influence their viewing experiences and point out that motivations such as relaxation, alleviating boredom, and escapism contribute to binge-watching behavior. Moreover, in TV drama research, Ort et al. (2021) find that problematic viewing behaviors are positively associated with motivations for engaging in high-dose watching sessions.

Meanwhile, Chan-Olmsted and Wang (2022) examine consumption motivations and usage behaviors among podcast audiences. The findings from Chan-Olmsted and Wang (2022) indicate that the most significant factors influencing podcast usage are information, entertainment, and audio platform superiority. Furthermore, listening behaviors are shown to be influenced by these motivations. Similarly, Zheng et al. (2023) investigate the antecedents of viewer engagement in live streaming, and their analytical results demonstrate that audience behavior in live streaming is positively influenced by motivations related to social presence, involvement, streamer appeal, and streamer knowledge.

On top of that, according to Hu (2021) and Wang (2022), the primary motivations for viewing web dramas include entertainment, relaxation, escapism, passing time,

information seeking, and social interaction. Consequently, it can be inferred that web drama exposure is influenced by viewing motivation in the context of Chinese web dramas. Based on the aforementioned studies, the second research hypothesis is proposed as follows:

Hypothesis 2: Web drama viewing motivation has an impact on web drama exposure.

In light of UGT, the social and psychological origins of needs give rise to expectations regarding mass media or other sources, leading to differential exposure (or engagement in alternative activities), which in turn results in need gratification and other outcomes (McQuail & Deuze, 2020; Katz et al., 1974; West & Turner, 2020). Given that various forms of media exposure yield need gratification and associated consequences, and considering that audience satisfaction is equivalent to gratification following media exposure (Bae, 2018; Perse & Ferguson, 2000), it can be inferred that media exposure may positively influence audience satisfaction with media content.

Meanwhile, several empirical studies have focused on examining the relationship between media exposure and audience satisfaction with media content. To explore youth satisfaction in adopting new media, Haqqu et al. (2019) indicate that greater exposure to YouTube is associated with higher levels of satisfaction, suggesting that

increased usage of YouTube contributes to enhanced user satisfaction. Furthermore, Suh et al. (2019) find that watching sports broadcasts enhances audience satisfaction with sporting events. Additionally, Kim and Kim (2020a) observe that during the viewing of travel reality variety programs, perceived reality presence increases enjoyment and engagement, thereby enhancing viewing satisfaction. This finding from Kim and Kim (2020a) implies that audience satisfaction with travel reality programs is positively influenced by viewer engagement behaviors.

Besides that, Tkalac Verčič and Špoljarić (2020) claim that the participants obtain high levels of satisfaction with rich communication channels, on the contrary, the single communication channel result in their low satisfaction level. In addition, focusing on predicting audience gifting behavior in media streaming live sports, Liu et al. (2022) find that viewers' perceived value of the live sports experience significantly influences their satisfaction. Building on this finding, it can be reasonably inferred that viewing behavior during live sports streaming also contributes to audience satisfaction, as perceived value is largely derived from how audiences engage with and experience the streamed content.

Furthermore, in an effort to examine the relationship between news media exposure and life satisfaction during the COVID-19 pandemic, Iwanowska et al. (2023) report a significant positive association between the two variables. Drawing on these prior findings, this study proposes the following third research hypothesis:

Hypothesis 3: Web drama exposure influences web drama audience satisfaction.

In accordance with UGT, the social and psychological origins of needs that give rise to expectations of mass media or other sources lead to differential exposure or engagement in alternative activities (McQuail & Deuze, 2020; Katz et al., 1974; West & Turner, 2020). This suggests that motivation for using a particular medium may contribute to exposure to other media. Meanwhile, research has shown that the advantages of social media, including convenience, utility, and opportunities for social interaction, encourage and facilitate increased usage (Falgoust, 2022; Oeldorf-Hirsch & Srinivasan, 2021).

Besides that, social media engagement within the web drama content domain is actively embraced by audiences as a means to extend web drama exposure, according to CCT research (Jiang & Liu, 2022; Neyazi et al., 2019; Zhang et al., 2020). Consequently, it could be inferred that motivation for web drama viewing contributes to audience social media engagement.

Furthermore, similar findings have been reported in relevant studies on social TV. According to Odunaiya et al. (2020), social TV, as an integration of television and social media, has significantly enhanced viewers' connectivity and engagement with content through social media interactions. Regarded as a multi-screen and

multitasking environment, social TV empowers viewers to follow their preferred shows, share TV-related content, transform viewing experiences into online events, and interact with other audiences before, during, and after broadcasts (Odunaiya et al., 2020). Notably, social TV involves audience interaction across all stages of the viewing process. In other words, it encompasses the engagement of TV audiences on social media platforms.

Research on social TV has demonstrated that viewers' motivations for watching content significantly influence their engagement with social media platforms. Lin et al. (2018) found that social entertainment, a key motivational factor, effectively predicts audience participation in social TV activities. Extending this line of inquiry to sports programming within social live streaming services, which represent an emerging form of social networking, Kim and Kim (2020b) identified emotional, social, tension-relief, and personal motivations as significant antecedents of flow experience, which in turn enhances user engagement in live-streamed sporting events.

In addition, Habes (2019) highlights that individual motivations significantly influence general social media use as well as engagement with social TV. Key motivational factors identified by Habes (2019) include leisure, daily routines, access to information, educational interests, time availability, amusement, escapism, and the desire to form new social connections, all of which play a critical role in shaping

audience participation in social TV. These motivations facilitate viewers' ability to establish and maintain interactions on social live streaming platforms. Grounded in UGT, Khoshaim (2020) developed a motivation scale to assess user engagement in second-screen experiences, defined as the concurrent use of secondary devices to discuss television content. The study confirms participant support for all proposed motivations, revealing that entertainment needs are prioritized over cognitive needs, which in turn slightly outweigh motivations related to personal identity and social integration.

Meanwhile, building on UGT, Kim et al. (2021a) examine the influence of social TV viewing motivations on audience choices between public social media platforms, such as Twitter news feeds and Facebook timelines, and private messaging platforms like WhatsApp. Their findings indicate that distinct viewing motivations are associated with preferences for specific types of platforms. Furthermore, recent research into the motivations underlying social TV use has sought to enhance understanding of contemporary audience behavior (Tsai & Lin, 2023).

In the meantime, Dong and Xie (2024) argue that viewing motivations among short video audiences, such as exploring novel content, maintaining habitual routines, sustaining social relationships, relieving stress, passing time, and escaping from reality, influence their engagement on Chinese TikTok. Consequently, audience

viewing motivation can be regarded as a key determinant of social media engagement.

On top of that, according to Hu (2021) and Wang (2022), the primary motivations for viewing web dramas include entertainment, relaxation, escapism, passing time, information seeking, and social interaction. Meanwhile, based on UGT, motivation for using a particular medium may contribute to exposure to other media (McQuail & Deuze, 2020; Katz et al., 1974; West & Turner, 2020). Accordingly, audience's motivation for web drama viewing may have an influence on their social media engagement. Based on the aforementioned studies, this investigation formulates the fourth research hypothesis as follows:

Hypothesis 4: Web drama viewing motivation impacts on audience social media engagement.

As stated earlier, CCT research indicates that web drama audience adopts social media engagement in the web drama content domain as the extension of web drama exposure (Jiang & Liu, 2022; Neyazi et al., 2019; Zhang et al., 2020). Meanwhile, building on UGT, differential media exposures result in need gratification and other consequences (McQuail & Deuze, 2020; Katz et al., 1974; West & Turner, 2020). The integration of CCT and UGT suggests that audience social media engagement, particularly in relation to web drama content, can lead to need gratification. In the

meantime, as has been mentioned above, the audience satisfaction is equivalent to gratification following media exposure (Bae, 2018; Perse & Ferguson, 2000). Consequently, it can be postulated that audience social media engagement may positively affect web drama audience satisfaction.

At the same time, this postulation is supported by empirical evidence. Yoo (2011) finds that the adoption of interactive technologies enhances the gratifications derived from media use, with audience interactivity serving as a key contributor to these outcomes. This suggests a positive relationship between social media engagement within a specific content domain and the level of satisfaction derived from it. Meanwhile, research by Suh et al. (2019) demonstrates that sharing social viewing experiences during sports broadcasting positively influences user satisfaction. Specifically, when audiences express their opinions on social media following televised sporting events, their viewing satisfaction tends to be higher. In other words, the combination of watching sports broadcasts and engaging with others on social media to share viewing experiences enhances audience satisfaction with the sporting events.

In addition, recent studies have employed social media comments on specific research subjects to predict user satisfaction, suggesting that audience engagement with a particular content domain on social media positively influences their satisfaction with it. In a study aimed at predicting customer satisfaction through the

technical features of online textual reviews and user involvement on social media, Zhao et al. (2019) found that customers' level of involvement in reviews significantly enhances their overall satisfaction.

Moreover, focusing on sports content within social live streaming services, which are regarded as an emerging form of social networking, Kim and Kim (2020b) find that user satisfaction with these platforms is positively influenced by flow experiences during live streaming use. Meanwhile, in their study on predicting audience gifting behavior, Liu et al. (2022) observe that audience activities on social media platforms, such as sharing emotional reactions and sending virtual gifts in real time, reflect the extent of satisfaction with the viewing experience. This indicates that audience satisfaction can be shaped by their level of engagement on social media.

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Furthermore, in a study examining the effects of customer satisfaction and social media engagement on repurchase intentions within the hotel industry, Majeed et al. (2022) demonstrate that customer satisfaction exerts a positive and significant influence on various dimensions of customer engagement on social media. By extension, it can be inferred that social media engagement may reciprocally enhance customer satisfaction. In addition, Zhao et al. (2023) argue that engagement with social networking sites, such as WeChat, WhatsApp, Facebook, Twitter, QQ, Instagram, LinkedIn, and Sina Weibo, is positively associated with life satisfaction,

suggesting that active participation in these platforms contributes to higher levels of personal well-being.

Additionally, Meng et al. (2023) find that adolescents' use of mobile social media is positively associated with life satisfaction, thereby enhancing understanding of the relationship between mobile social media engagement and well-being. Furthermore, Cary et al. (2024) examine multidimensional patterns of Instagram use and report that higher levels of life satisfaction are linked to more frequent receipt of communications and greater engagement in browsing relevant content on the platform. Building on these findings, the present study proposes the following fifth research hypothesis:

Hypothesis 5: Audience social media engagement affects web drama audience satisfaction.

Building on CCT, various media coexist synergistically to shape audiences' information-seeking behaviors. Individuals who rely on one medium for information in a specific domain are more likely to adopt additional media that provide content related to the same area (Jiang & Liu, 2022; Neyazi et al., 2019; Zhang et al., 2020). For example, audiences engaged with online news on particular topics tend to also seek out coverage of those topics through traditional media sources (Jiang & Liu, 2022; Neyazi et al., 2019; Zhang et al., 2020). By extension, audiences of web

dramas may extend their exposure to web drama content by engaging with other audience members in the same content domain on social media. Therefore, based on CCT, this study postulates that web drama exposure influences audience social media engagement.

In recent years, in response to the widespread phenomenon of audiences engaging in social media interactions following exposure to television programs within specific content domains, social TV research has increasingly focused on understanding this behavior (Elareshi et al., 2022; Habes et al., 2022). For instance, Lin et al. (2018), in their investigation of viewers' social TV participation, found that participants extend their viewing experiences by interacting with both the programs and other viewers on program-related websites and social media platforms. These empirical findings provide further evidence that social media are playing an increasingly central role in the television viewing experience.

In addition, Suh et al. (2019) argue that audiences can access real-time information about the television programs they are watching through social media, as well as share viewing experiences and emotional reactions. Meanwhile, it has been observed that since 2013, Nielsen, a U.S.-based television ratings company, has actively tracked the development of social TV (Nee & Barker, 2019).

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Furthermore, existing literature highlights the influence of media exposure on social media engagement. Currently, millions of individuals use platforms such as Facebook and Twitter to share their television viewing experiences with others (Odunaiya et al., 2020). Consistent with findings from Nagy and Midha (2014), Lin et al. (2018), and Odunaiya et al. (2020), over 80% of primetime Twitter users regularly post about television programs. Among these users, 72% tweet while watching live broadcasts, and 58% engage in posting during consumption of content from streaming platforms such as Netflix. Moreover, more than 60% of smartphone and tablet users employ their devices as second screens when viewing television shows, with nearly one-quarter of their multiscreen activities relating to TV-related content (Lin et al., 2018; Nagy & Midha, 2014; Odunaiya et al., 2020).

Meanwhile, drawing on the findings of Nee and Barker (2019), 45% of participants from the Middle East and 75% from the United States report using a second screen to engage in communication or social media interaction related to their television viewing. These patterns of digital connectedness appear to be both globally widespread and, to some extent, shaped by generational differences (Nee & Barker, 2019). Taken together, these results suggest that exposure to TV shows and web video programs influences audience engagement on social media.

In the meantime, García-Perdomo (2021) notes that social media not only plays a crucial role in video engagement and distribution but also provides a powerful

platform for sharing social videos. Furthermore, by analyzing the relationship between digital news coverage and audience motivation to engage on social media, Mourão and Brown (2021) find that news reports on protests can increase the likelihood of individuals reading, liking, sharing, and commenting on protest-related stories online. The authors emphasize that media coverage significantly influences user engagement behaviors on social media platforms.

Moreover, as noted by Tsai and Lin (2023), greater exposure to TV entertainment programs is associated with an increase in social media comments. Extending this insight, Tsai and Lin (2023) suggest that by actively engaging with audiences through social media platforms, media stakeholders can create and capitalize on more opportunities to enhance the popularity of their TV entertainment programs. In light of the above studies, the sixth research hypothesis is therefore proposed as follows:

Hypothesis 6: Web drama exposure has an influence on audience social media engagement.

2.2.12.2 Research Hypotheses on the Mediating Effects of Web Drama Exposure and Audience Social Media Engagement

First and foremost, based on UGT, the social and psychological origins of needs that generate expectations from mass media or other sources lead to differential exposure

(or engagement in alternative activities), ultimately resulting in need gratification and associated consequences (McQuail & Deuze, 2020; Katz et al., 1974; West & Turner, 2020). This suggests that media exposure may play a mediating role in the relationship between audience motivation and audience satisfaction.

Moreover, the previous studies indicate that web drama viewing motivation has an impact on web drama exposure (Lin et al., 2018; Tefertiller & Sheehan, 2019), which affects web drama audience satisfaction (Iwanowska et al., 2023; Liu et al., 2022; Tkalac Verčič & Špoljarić, 2020). Meanwhile, there are some studies on the investigation and analysis of the mediating effect of media exposure. Borghese et al. (2015) point out that, as a lifestyle behaviour, TV viewing plays a mediating role in the relationship between TV in the bedroom and adiposity among Canadian females.

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Do Carmo et al. (2020) propose that TV viewing duration plays a key mediating role in the relationship between perceived neighborhood insecurity and body mass index in school-aged children. Parents who perceive the external environment as unsafe may limit their children's outdoor physical activity and encourage greater time spent indoors, during which sedentary behaviors such as prolonged television watching are more likely to occur, thereby contributing to lower levels of physical activity (Do Carmo et al., 2020).

To examine the relationships among impulsive online buying tendency, impulsive online purchasing behavior, and customer satisfaction, Goel et al. (2022) find that impulsive online purchasing mediates the link between predisposition toward impulsive buying and satisfaction levels. The body of literature cited above further supports the presence of a mediating role of media exposure in such consumer behavior dynamics.

Furthermore, Tefertiller and Sheehan (2019) indicate that certain motivations for TV viewing are positively associated with viewing patterns, including audience demographics, behavioral characteristics, program genre, streaming consumption, and traditional viewing methods. Concurrently, greater involvement in programming content is shown to enhance viewer satisfaction (Tefertiller & Sheehan, 2019). This research draws on the findings of Borghese et al. (2015), Do Carmo et al. (2020), Goel et al. (2022), and Tefertiller and Sheehan (2019) to posit that media viewing may serve as a mediator in the relationship between viewing motivation and audience satisfaction.

Besides that, according to Kim and Kim (2020a), presence, which is conceptualized as a core component of viewing experience, mediates the relationship between viewing motivation and viewing satisfaction. In the present study, viewing experience is largely equivalent to web drama exposure. Therefore, it can be hypothesized that the effect of web drama viewing motivation on viewing

satisfaction is mediated by web drama exposure. Building on the theoretical and empirical foundations discussed above, the following seventh research hypothesis is proposed:

Hypothesis 7: Web drama exposure mediates the relationship between web drama viewing motivation and web drama audience satisfaction.

Drawing on UGT, the social and psychological origins of needs that underlie individuals' expectations toward mass media or alternative sources contribute to differential media exposure or engagement in alternative activities, ultimately leading to gratification of those needs and associated outcomes (McQuail & Deuze, 2020; Katz et al., 1974; West & Turner, 2020). Concurrently, grounded in CCT, audiences of web dramas extend their exposure through active participation on social media platforms (Jiang & Liu, 2022; Neyazi et al., 2019; Zhang et al., 2020).

Recent studies indicate that motivations for viewing web dramas are positively associated with audience engagement on social media platforms (Dong & Xie, 2024; Falgoust, 2022; Tsai & Lin, 2023), which in turn contributes to variations in web drama audience satisfaction (Cary et al., 2024; Meng et al., 2023; Zhao et al., 2023). Therefore, it can be hypothesized that audience social media engagement mediates the relationship between web drama viewing motivation and audience satisfaction.

Moreover, several studies have highlighted the mediating function of social media engagement in various psychological and behavioral contexts. Lisitsa et al. (2020) find that social media use serves as a mediator between age and feelings of loneliness. To better understand how individuals' responses to the COVID-19 pandemic influence worker well-being, Khatri et al. (2021) propose a mediated model in which social media engagement functions as the mediating variable, concluding that it significantly mediates the relationship between pandemic-related reactions and employee well-being during the crisis period.

Furthermore, in examining the relationship between social media adoption and the performance of small and medium-sized enterprises, Qalati et al. (2021) treat social media adoption as a mediating variable and find that it significantly mediates the influence of technology, organizational, and environmental factors on the performance of small and medium-sized enterprises.

In addition, Susanto et al. (2021) propose that social media usage mediates the relationship between entrepreneurial orientation and the performance of small and medium-sized enterprises, emphasizing that leveraging social media enables firms to access real-time market knowledge. Entrepreneurial orientation could be regarded as a motivational driver, whereas performance in small and medium-sized enterprises may encompass satisfaction. Furthermore, Tylka et al. (2023) demonstrate that social media usage functions as a mediator in the link between motivations for using social

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media and individuals' body satisfaction. Drawing on this body of evidence, the present study proposes the following eighth research hypothesis:

Hypothesis 8: Audience social media engagement mediates the relationship between web drama viewing motivation and web drama audience satisfaction.

Grounded in UGT and CCT, as well as empirical findings from Cary et al. (2024), Liu et al. (2022), Majeed et al. (2022), Meng et al. (2023), and Zhao et al. (2023), this study posits that web drama viewing motivation positively influences web drama exposure. Increased exposure, in turn, enhances audience engagement on social media platforms, which subsequently contributes to higher levels of viewer satisfaction. Building on these direct pathways, the present research proposes an indirect association: web drama viewing motivation exerts an indirect effect on audience satisfaction through a sequential mediation process involving web drama exposure and audience social media engagement.

Moreover, prior studies have demonstrated that media exposure mediates the relationship between viewing motivation and audience satisfaction (Borghese et al., 2015; Do Carmo et al., 2020). Concurrently, existing research suggests that audience engagement on social media serves as a mediator in the link between viewing motivation and audience satisfaction (Khatri et al., 2021; Susanto et al., 2021; Tylka et al., 2023).

Furthermore, social TV is defined as audience engagement with televised content through social media platforms (Nee & Barker, 2019). Viewers actively share their reactions and personal insights regarding the programs they are watching, while simultaneously seeking additional information about them in real time via social media (Suh et al., 2019). Millions of viewers use social media to communicate their television viewing experiences and interact with others who are consuming the same content (Odunaiya et al., 2020). Collectively, research on social TV indicates that media exposure contributes to increased levels of audience social media engagement.

Moreover, Ji (2023) finds that the viewing experiences of Chinese web drama audiences are often rooted in their underlying needs and are frequently shared across various social media platforms, such as Weibo and Douban. Taking *Love Between Fairy and Devil* as an example, the series generated nearly 200 related entries on the Weibo Hot Search list by September 5, 2022, shortly after its release.

Meanwhile, building on the findings of Lin et al. (2016), audience engagement with programs and other viewers is facilitated through social TV participation, which extends the viewing experience. Furthermore, participation in social TV activities has been shown to positively influence audience satisfaction with their preferred programs (Lin et al., 2016). The results reported by Lin et al. (2016) indicate that

social TV participation mediates the relationship between viewing experience and audience satisfaction with favorite content.

On top of that, according to Kim and Kim (2020a), presence is conceptualized as a dimension of viewing experience that includes involvement, attention, and engagement with reality programs, and it mediates the relationship between viewing motivation for travel-based reality variety shows and audience satisfaction. Given that media exposure and social media engagement are conceptually aligned with aspects of viewing experience, the present study posits the sequential mediating role of web drama exposure and audience social media engagement in the relationship between viewing motivation and audience satisfaction. Drawing on the body of evidence reviewed above, the following ninth research hypothesis is proposed:

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Hypothesis 9: Web drama viewing motivation are indirectly related to web drama audience satisfaction, sequentially mediated through web drama exposure and audience social media engagement.

2.2.12.3 Research Hypotheses on the Moderating Effect of Social Media Community Size

To date, many previous studies have adopted social media community size as a moderator (Dolan, 2015; Jiang et al., 2019; Nepomuceno et al., 2020; Yang et al.,

2016). Therefore, the present study follows these prior studies by adopting social media community size as the moderating variable.

According to UGT, variations in media exposure or engagement in alternative activities result in differing levels of need gratification and associated outcomes (McQuail & Deuze, 2020; Katz et al., 1974; West & Turner, 2020). Concurrently, CCT highlights the importance of social media engagement as an extension of web drama consumption, shaping audience perceptions and experiences (Jiang & Liu, 2022; Neyazi et al., 2019; Zhang et al., 2020). The integration of UGT and CCT suggests that social media community size may serve as an antecedent to audience satisfaction.

According to Yang et al. (2016), online community affiliation moderates the relationship between motivation, including interactivity and reciprocity, and satisfaction. First, online community affiliation weakens the positive relationship between interactivity and satisfaction; that is, as interactivity increases, individuals with low online community affiliation report higher levels of satisfaction compared to those with high online community affiliation. Meanwhile, online community affiliation strengthens the positive relationship between reciprocity and satisfaction; that is, as reciprocity increases, individuals with high online community affiliation report higher levels of satisfaction compared to those with low online community affiliation.

Moreover, Jiang et al. (2019) indicate that the association between volunteering behaviour and life satisfaction is moderated by changes in social network size. Specifically, the effect of volunteering behaviour on life satisfaction is positive under conditions of low change in social network size, whereas volunteering behaviour negatively influences life satisfaction under conditions of high change in social network size. Meanwhile, volunteering behaviour is driven by diverse motivations. Accordingly, it can be inferred that social network size may moderate the relationship between volunteering motivations and life satisfaction.

In addition, Liu and Pan (2020) argue that the effect of linking social capital on life satisfaction among rural-to-urban migrants is moderated by friendship network size, such that this positive association diminishes as friendship network size increases. Specifically, as linking social capital increases, individuals with a lower friendship network size report a greater increase in life satisfaction.

Furthermore, Zhang et al. (2022) report that social support can amplify the association between intrinsic community-related motivation and life satisfaction, specifically, individuals who perceive greater social support could experience higher life satisfaction as intrinsic community-related motivation increases. Meanwhile, Morelli et al. (2023) find that the association between motivation and academic satisfaction is moderated by the number of friends. Specifically, this moderator

amplifies the negative relationship between the two variables. Students with a larger number of friends at university exhibit a greater decline in satisfaction as motivation increases.

Social media community size is, to some extent, indicative of social network size, social support, and online community affiliation. Consequently, it may be inferred that the direct effect of web drama viewing motivation on web drama audience satisfaction is moderated by social media community size. Based on the literature reviewed above, the tenth research hypothesis is proposed as follows:

Hypothesis 10: Social media community size moderates the direct effect of web drama viewing motivation on web drama audience satisfaction.

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According to UGT, audience demands that generate expectations of mass media or other information sources lead to differential exposure or engagement in alternative activities (McQuail & Deuze, 2020; Katz et al., 1974; West & Turner, 2020). Meanwhile, CCT suggests that audiences who use one medium to obtain information in a particular domain are likely to adopt additional media that provide content within the same area (Jiang & Liu, 2022; Neyazi et al., 2019; Zhang et al., 2020).

Meanwhile, social media community size has been used as a moderating variable in prior studies (Jiang et al., 2019; Nepomuceno et al., 2020; Yang et al., 2016).

Drawing on UGT, CCT and related literature, it can be postulated that social media community size may moderate the relationship between web drama exposure and audience social media engagement.

According to Arya et al. (2019), the presence of online brand community positively moderates the relationship between perceived brand authenticity and consumers' brand attachment behavior. Concretely, compared to customers who engage in passive participation, those who actively participate in a brand's online communities experience greater brand attachment as brand authenticity increases. Social media community size is, to some extent, indicative of online brand community, as a consequence, it can be postulated that the relationship between web drama exposure and audience social media engagement is moderated by social media community size.

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In the meantime, the empirical study made by Dolan (2015) claims that the social media community size positively moderates the relationship between entertaining content and social media engagement behavior through the empirical study. Specifically, compared to entertaining content in medium-sized or small-sized social media communities, such content in large-sized social media communities has a greater effect on social media engagement behavior.

Additionally, according to Nepomuceno et al. (2020), social media content is not associated with commercial performance in large online communities; however, the relationship between social media content and commercial performance is moderated by online community size in medium-sized communities. Specifically, in medium-sized communities, the increase in social media content leads to higher levels of commercial performance. Based on the literature reviewed above, the eleventh research hypothesis is proposed as follows:

Hypothesis 11: Social media community size moderates the relationship between web drama exposure and audience social media engagement.

Among the eleven hypotheses presented above, H1 through H6 align with the first research question and the first research objective outlined in Chapter One. H7 through H9 correspond to the second research question and the second research objective, while H10 and H11 address the third research question and the third research objective. In theoretical grounding, H1, H2, H3, and H7 are derived from UGT, whereas H6 is informed by CCT. Hypotheses H4, H5, H8, H9, H10, and H11 are grounded in both UGT and CCT.

In addition, the final research question and research objective of this study fall within the scope of exploratory research. Exploratory research is conducted to satisfy the researcher's curiosity and need for deeper understanding, assess the feasibility of

undertaking a larger-scale study, and develop methods for potential follow-up research (Babbie, 2020; Boyle & Schmierbach, 2024). As exploratory research does not involve predefined hypotheses (Haile, 2023), the current study does not formulate hypotheses for these components.

2.2.13 The Hypothesized Predictive Model of the Study

Based on the established conceptual model and the eleven hypotheses above, this study proposes the hypothesized predictive model, which is exhibited in Figure 2.3 below.

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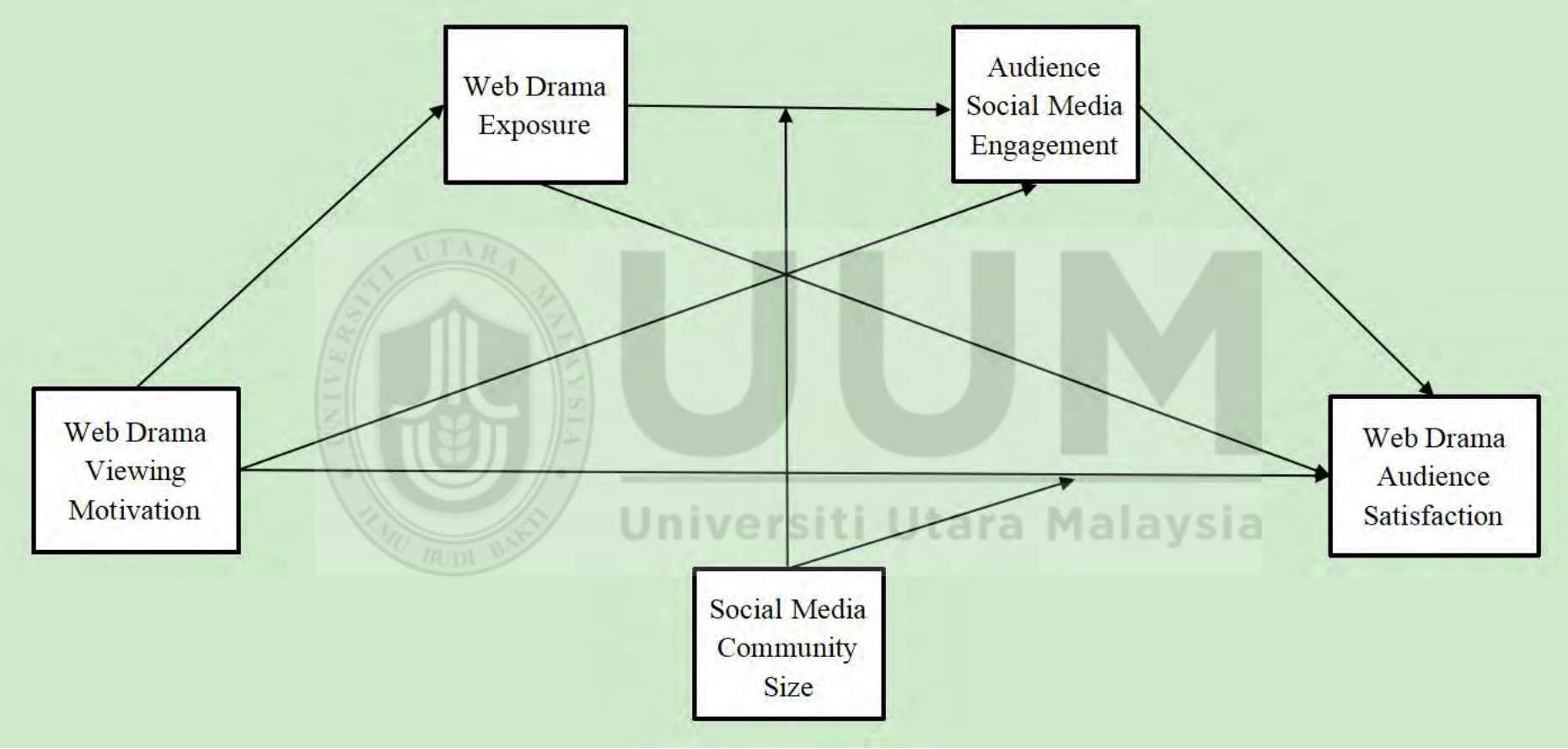


Figure 2.3 The Hypothesized Predictive Model of the Study

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If the conceptual model of this study is supported by the results of hypothesis testing, the present study will adopt the hypothesized predictive model as the model for explaining audience satisfaction in Chinese web dramas.

2.3 Chapter Summary

This chapter is comprised of three sections. The first section provides the introduction of this chapter. Following that, the second section is the literature review on Chinese web drama, foreign web drama, audience satisfaction, viewing motivation, media exposure, social media engagement, social media community size, media effects, and social media big data analytics approach. Meanwhile, UGT and CCT are reviewed in sequence as the components of theoretical framework of this study. Subsequent to the literature review, the second section offers the conceptual model of the study, the development of research hypothesis and the hypothesized predictive model. In the end, the summary of this chapter is exhibited in the third section. In the next chapter, the present study will state the research methodology in order to test the eleven hypotheses proposed.

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CHAPTER THREE

RESEARCH METHODOLOGY

3.1 Introduction

This chapter outlines the research methodology employed in the present study, explaining how the methods were implemented to achieve the research aim of this study. Specifically, this includes research philosophy, research design, operationalization of the constructs, data collection procedures, statistical analysis procedures, the application of PLS-SEM, assessment of the measurement model, hypothesis testing using structural equation model, the pilot study, and ethical considerations.

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3.2 Research Philosophy

Research philosophy denotes a set of fundamental beliefs that guide the design and conduct of a research study (Tamminen & Poucher, 2020). The selection of a specific research philosophy in a given study hinges on the knowledge under investigation (Shan, 2022; Tamminen & Poucher, 2020). As an empirical philosophy, positivism denotes an epistemological position that supports the application of natural science techniques to the study of social reality and beyond (Clark et al., 2022). Its application in society is extensive, particularly in social research (Maretha, 2023).

According to Clark et al. (2022) and Maretha (2023), in positivist research, genuine knowledge is verified through sensory observation, and the aim of theory is to generate testable hypotheses that enable the evaluation of explanations for patterns and regularities. They point out that science must be conducted objectively, and researchers should employ scientific statements rather than normative ones. This study is consistent with all the aforementioned principles of positivism. Therefore, positivism is adopted as the research paradigm. Specifically, this study employs positivism to focus on the research aim: formulating a comprehensive predictive model of audience satisfaction in Chinese web dramas through a big data analytics approach, informed by UGT and CCT.

Moreover, according to Babbie (2020) and Clark et al. (2022), there are two logical models: deduction and induction. Deduction is defined as a logical approach in which specific hypotheses are derived from general theoretical principles. The process proceeds from theory to hypothesis, then to data collection, to findings, and finally to the confirmation or rejection of hypotheses, followed by theory refinement. In the present study, eleven hypotheses are developed within the theoretical framework informed by UGT and CCT, with the aim of generating findings and conclusions through hypothesis testing via big data collection and statistical analysis. Given that the research follows a theory-driven path and emphasizes empirical validation, it aligns clearly with the deductive model. Therefore, deduction is adopted as the logical model guiding this study.

3.3 Research Design

Research design is defined as the procedural framework that determines what aspects the researcher observes, from whom data are collected, and why observations are made (Babbie, 2020; Croucher & Cronn-Mills, 2024). It involves a series of considerations regarding the research topic, population, methods, research purpose, and related factors. A research design provides a structured approach for collecting and analyzing data, and the choice of design reflects the priorities and significance researchers assign to specific elements of the research process (Clark et al., 2022).

The purpose of this study is to develop a predictive model of audience satisfaction in Chinese web dramas using a big data analytics approach. To achieve this, the study clarifies the correlations among web drama audience satisfaction, web drama viewing motivation, web drama exposure, audience social media engagement, and social media community size. Therefore, this research design integrates the description, explanation and exploration (Babbie, 2020; Boyle & Schmierbach, 2024).

Specifically, to address the research questions and objectives of this study, a quantitative research approach is employed. Quantitative research involves the numerical representation and analysis of observations in order to describe, explain, and explore the phenomena they represent (Babbie, 2020; Scharrer &

Ramasubramanian, 2021). This study attempts to test eleven hypotheses across five constructs through the numerical processing of data using a big data analytics approach, making it an appropriate methodological choice.

Furthermore, the integration of big data analytics into quantitative research has brought significant advancements to the social sciences (Song, 2023; Tang et al., 2022; Zhou, 2022). According to Stieglitz et al. (2018), the big data analytics process consists of four distinct phases: data discovery, collection, preparation, and analysis. Therefore, this section outlines the components of the research design, including the research method, time dimension, unit of analysis, population and sampling strategy, sampling frame, sample size, and sampling technique.

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3.3.1 Research Approach

This study adopts a quantitative research approach. As previously noted, quantitative research is defined as a method that emphasizes numerical data to describe and explain phenomena (Babbie, 2020; Scharrer & Ramasubramanian, 2021). The study aims to construct a comprehensive predictive model of audience satisfaction in Chinese web dramas using a big data analytics approach. Given that the representation and processing of observations derived from big data are essential for describing and explaining the phenomena under investigation, quantitative analysis is employed.

Specifically, in response to the four distinct research questions and objectives, the present study attempts to adopt the quantitative research utilizing big data analytics approach to collect large-scale data for purposes of description, explanation, and exploration (Babbie, 2020). In accordance with Babbie (2020), the big data analytics approach is currently evolving. As discussed by Boyle and Schmierbach (2024), computer-aided techniques are increasingly adopted due to the growing availability of large-scale public data from social media and other sources classified as big data. Therefore, employing the quantitative research utilizing big data analytics approach is appropriate for this study.

3.3.2 Time Dimension

Investigators can address the temporal dimension through two primary research designs: cross-sectional and longitudinal studies (Babbie, 2020; Boyle & Schmierbach, 2024). Specifically, a cross-sectional study is a research design characterized by the collection of data from a sample of individuals at a single point in time, aiming to quantify relationships among two or more variables and to systematically examine them for patterns of association (Babbie, 2020; Clark et al., 2022). In contrast, a longitudinal study is a research design characterized by the systematic collection of data from a sample at two or more distinct time points over a defined period, thereby enabling the examination of temporal changes and developmental trajectories (Babbie, 2020; Clark et al., 2022).

This study employs a cross-sectional design. Specifically, data are collected from a sample of individuals at a single point in time to quantify relationships among variables and to systematically examine them, thereby providing a snapshot of the phenomena under investigation. It is worth noting that, although the data are collected at a single time point in this study, the process may require considerable time due to limitations in web crawling technology.

3.3.3 Unit of Analysis

The unit of analysis serves to investigate and summarize the characteristics of similar entities while explaining differences among them (Babbie, 2020; Boyle & Schmierbach, 2024). In social research, individuals, groups, organizations, social interactions, or social artifacts can function as units of analysis. The most straightforward approach to identifying the unit of analysis is to begin with the variables central to the study (Babbie, 2020; Boyle & Schmierbach, 2024).

First, the unit of analysis is determined by the research problem (Kumar, 2018). As stated by Kumar (2018), if an investigator seeks to explore why certain products achieve greater success than others, the product is the appropriate unit of analysis. Similarly, to address the issue of low audience satisfaction in certain Chinese web dramas, this study examines variations across individual web dramas with respect to the audience satisfaction variable and its antecedents. Therefore, the unit of analysis in this study is the individual web drama.

Moreover, by virtue of a big data analytics approach, viewers' motivations, behaviors, and satisfaction have been aggregated to construct measurable variables for each web drama, including viewing satisfaction, viewing motivation, exposure, and audience social media engagement. These variables for each web drama can be measured using real-time statistical datasets, including those derived from large-scale social media comments, social media metrics, major search engines, and professional big data platforms, and are subsequently incorporated into statistical analysis and modeling. As a result, the individual web drama serves as the unit of analysis in this study.

In addition, similar studies provide valuable references for the present study. Hu (2020) employs individual TV drama as the unit of analysis to examine the factors influencing TV drama ratings, thereby facilitating more accurate predictions of audience viewership. Additionally, Zhou and Zhao (2021) employ individual TV drama as the unit of analysis to explore media effect evaluation in audio-visual content through a big data analytics approach. Meanwhile, Mi et al. (2022) use individual web drama as the unit of analysis to forecast audience viewership based on comment sentiment analysis and an improved stacking ensemble model. Consequently, the individual web drama serves as the unit of analysis in this study.

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3.3.4 Identifying Population, Target Population and Sampling

After selecting the research method, this study proceeds to identify the population, target population and sampling. In terms of population, it refers to the complete set of units from which the sample is drawn. It is important to note that the population is not necessarily composed of individuals; nations, cities, regions, firms, and other social units may also constitute the population (Boyle & Schmierbach, 2024; Clark et al., 2022).

As previously stated, given that certain Chinese web dramas exhibit low audience satisfaction and have failed to gain favorable reception among viewers, this study aims to conduct predictive modeling of audience satisfaction in Chinese web dramas. Meanwhile, the individual web drama serves as the unit of analysis. Consequently, the population in this study comprises all Chinese web dramas.

The target population denotes a specific subset of the broader population that constitutes the primary focus of a study, characterized by attributes or criteria that directly align with the research aims or objectives (Willie, 2023). The target population enables researchers to concentrate their investigations on specific segments of the population that possess particular interest or significance (Willie, 2023).

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This study employs a big data analytics approach to conduct predictive modeling of audience satisfaction in Chinese web dramas. By leveraging comprehensive and reliable big data, this study focuses on a specific subset of Chinese web dramas that can effectively reflect audience viewing motivations, behaviors, and satisfaction. These data-rich cases enable the development of the study's predictive model in a systematic and robust manner. Consequently, all Chinese web dramas with accessible big data constitute the primary focus of this research.

Meanwhile, Chinese web dramas are broadcast on online video platforms, and given the presence of multiple platforms in China, this study focuses on dominant online video platforms when defining the target population. In recent years, Tencent Video (https://v.qq.com), iQIYI (https://www.iqiyi.com), Youku (https://www.youku.com), Mango TV (https://live.mgtv.com), Bilibili (https://www.bilibili.com), and SOHU Video (https://tv.sohu.com) are recognized as the dominant online video platforms in China, exhibiting a monopolistic market structure and holding a significant share of the market (Wang, 2023). Consequently, these six platforms serve as the primary sources of Chinese web dramas.

To be specific, Tencent Video, iQIYI, and Youku are primarily owned and supported by Tencent, Baidu, and Alibaba, which are China's largest Internet companies. These platforms are regarded as mainstream and widely used web video platforms (Frater, 2020; Zhang, 2022), continuously offering a wide range of Chinese web dramas to

audiences (Fung, 2019; Huang et al., 2021; Johnson, 2023; Wang, 2023) and holding a prominent position in the web drama industry. In addition, Bilibili, recognized as a video-sharing platform popular among young users, is China's largest professional user-generated content platform, attracting numerous video content creators (Han et al., 2021).

Although Mango TV currently ranks fourth in the Chinese domestic market, it is the only streaming platform capable of competing with the three leading private platforms: iQIYI, Youku, and Tencent Video. Despite its current position, Mango TV remains the sole media platform able to rival these major video service providers (Han, 2023). SOHU Video also maintains a presence among China's major video websites (Chen et al., 2022; Liu, 2021). In summary, the target population of this study includes all Chinese web dramas with accessible big data from Tencent Video, iQIYI, Youku, Mango TV, Bilibili, and SOHU Video.

With regard to sampling, it refers to the process of selecting a subset of the target population (Babbie, 2020; Turner, 2020). A smaller group is typically relied upon for data collection in most research projects because it is often impractical to include the entire population of interest (Babbie, 2020; Turner, 2020). Meanwhile, it should be emphasized that probability sampling is essential for generalizing from the sample to the population (Babbie, 2020; Boyle & Schmierbach, 2024).

As previously stated, this study leverages a big data analytics approach to eliminate reliance on sampling by enabling access to real-time, population-level statistical datasets, including those derived from large-scale social media comments, social media metrics, major search engines, and professional big data platforms. However, the practical constraint necessitates a sampling approach: comprehensively collecting real-time statistical data on the target population would exceed the available time and resource budget for this study.

To balance feasibility and representativeness, a probability sampling approach is adopted to ensure alignment with the target population's data distribution. The sample obtained via probability sampling continues to be populated with data collected through big data technologies, which ensures that the characteristics of the sample data in this study are highly consistent with those of the full-scale big data. As such, the sampled data remains capable of supporting the validity of the audience satisfaction prediction model.

Specifically, sampling is employed to select representative Chinese web dramas from major platforms, including Tencent Video, iQIYI, Youku, Mango TV, Bilibili, and SOHU Video. Consequently, the sample in this study comprises the sampled Chinese web dramas sourced from these platforms. Through sampling, researchers obtain a sample, which refers to a group of elements (Babbie, 2020), from which sample-level data are collected.

Correspondingly, the sample data consist of real-time statistical datasets from the sampled Chinese web dramas, including sample-level data collected from large-scale social media comments, social media metrics, major search engines, and professional big data platforms. Notably, large-scale social media comments constitute unstructured data that are exclusively textual in nature. Therefore, sentiment analysis techniques are employed to identify and quantify comments expressing motivational cues and satisfaction, thereby enabling the derivation of structured statistical datasets. Further details are elaborated in the following sections.

3.3.5 Sampling Frame

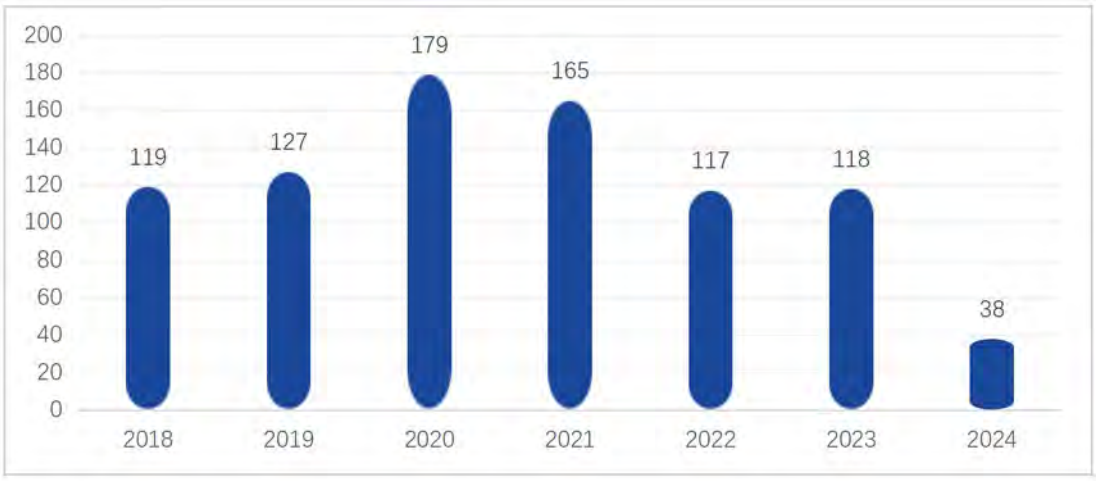
A sampling frame is defined as a list or quasi-list of all units in the population from which the sample is chosen (Babbie, 2020; Clark et al., 2022; Scharrer & Ramasubramanian, 2021). It outlines the characteristics that determine who is eligible to be included in the sample and what attributes can be used for selection (Clark et al., 2022). Ideally, the sampling frame should comprise all (or nearly all) members of the population; however, this is not always achievable in practice due to missing units (Babbie, 2020; Scharrer & Ramasubramanian, 2021).

Relying on the Chinese web drama database from the Maoyan app, the present study identifies all Chinese web dramas with accessible big data from Tencent Video, iQIYI, Youku, Mango TV, Bilibili, and SOHU Video, which serves as the sampling

frame. As an Internet-listed company, Maoyan provides comprehensive information, including movie trailers, box office data, and rankings and details of films and TV series. Specifically, the Maoyan app has offered information on all Chinese web dramas from Tencent Video, iQIYI, Youku, Mango TV, Bilibili, and SOHU Video since 2018.

Since 2018, Chinese web dramas have experienced significant development and growing popularity (Hu, 2021; Zhou & Zhi, 2020). Therefore, this Chinese web drama database, which contains all data since 2018, is the most comprehensive database currently available to researchers. Furthermore, drawing on the Chinese web drama database from the Maoyan app, the researcher filters out Chinese web dramas with accessible big data through a review of web drama information. Ultimately, 863 Chinese web dramas were identified as the sampling frame in this study, with data spanning from 2018 to 2024 (as of August 15, 2024) within this sampling frame (see Figure 3.1 below).

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Note: The horizontal axis represents the study period (by year), and the vertical axis denotes the annual count of Chinese web dramas.
Source: Maoyan app (2024)

Figure 3.1 Sampling Frame of the Study

3.3.6 Sample Size

One of the most frequent questions regarding research methods concerns the required sample size (Boyle & Schmierbach, 2024; Scharrer & Ramasubramanian, 2021). Sample size refers to the number of individuals participating in a study under consistent conditions. Larger samples are generally preferred because they enhance confidence in the results and improve statistical power (Boyle & Schmierbach, 2024). Nevertheless, in practice, decisions about sample size typically involve balancing the need for precision against constraints related to time and financial resources (Clark et al., 2022).

As previously stated, the target population of this study includes all Chinese web dramas with accessible big data from Tencent Video, iQIYI, Youku, Mango TV, Bilibili, and SOHU Video. Meanwhile, a sampling approach is adopted for the target

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population. The sample in this study comprises the sampled Chinese web dramas sourced from Tencent Video, iQIYI, Youku, Mango TV, Bilibili, and SOHU Video. To determine the appropriate sample size of Chinese web dramas for the current study, three criteria must be considered.

First, sample size requirements from prior relevant studies should be reviewed. Second, sample size estimation using G*Power software should be incorporated. Third, the sample size guidelines for partial least squares structural equation modeling (PLS-SEM), the statistical method employed in this study, must be adhered to.

In terms of sample size requirements from previous relevant studies, no established sample size criterion has been identified in prior research. Most related studies, such as Oh et al. (2016), Woo and Mishra (2020), and Tsai and Lin (2023), adopt case study designs. The study by Zhou and Zhao (2021), which is among the few available for reference, includes 30 samples, while another relevant study conducted by Mi et al. (2022) employs 152 samples.

Concerning the sample size estimation from G*Power software, G*Power software that is from Heinrich-Heine-Universität Düsseldorf in Germany is devoted to the estimation of sample size for various statistical methods due to its convenience, the steps in the sample size estimation process are from identifying research aim and

hypotheses to selecting appropriate statistical tests, and finally to inputting the number of predictors (Kang, 2021a). The latest version of G*Power which is utilized by this study is 3.1.9.7.

Regarding the present study, “F tests” is adopted as test family, “linear multiple regression: Fixed model, R^2 deviation from zero” is employed as statistic test, and “A priori: Compute required sample size - given α, power, and effect size” is embraced as type of power analysis, in the meantime, this investigation employs the medium f^2 effect size of 0.15, the α level of 0.05, the power value of 0.95, and 4 predictors as the input parameters (Bartlett, 2022; Chaokromthong & Sintao, 2021; Roni & Djajadikerta, 2021).

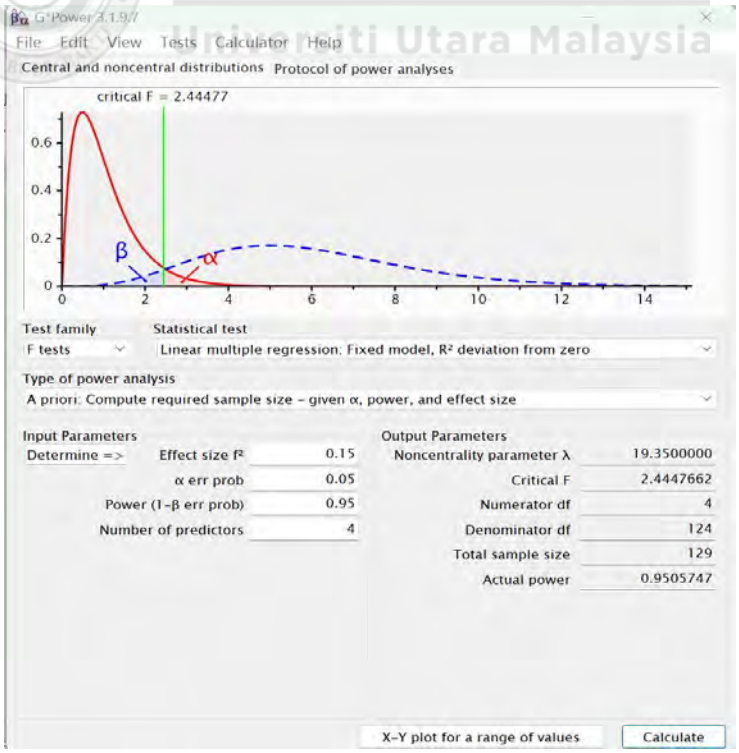


Figure 3.2 The Consequence of Sample Size Estimation from G*Power 3.1.9.7

Subsequent to clicking the “calculate” button, the researcher can obtain the outcome immediately. The consequence of sample size estimation of this study provided by G*Power 3.1.9.7 is 129, which is manifested by Figure 3.2 above. It implies that the sample size for this study ought to reach at least 129.

Regarding the requirement of sample size from PLS-SEM, with the evolution of it, Hair et al. (2019b) propose the following recommendations for minimal sample sizes in light of the model complexity and basic measurement model characteristics, which is manifested in Table 3.1 below. Considering that the model of this study contains five constructs and each of them is with more than three items (observed variables), a sample size of 100 can be regarded as the minimum sample size based on Table 3.1 below.

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In addition, the small sample size capability of PLS-SEM has received tremendous attention (Hair et al., 2019b). Concentrating on the requirement of sample size from PLS-SEM, Hair et al. (2022) introduce the often-cited 10 times rule which indicates the minimum sample size ought to be ten times the number of independent variables in the most complex regression in the PLS path model, it implies that a sample size of 40 is the minimum sample size of this study. However, according to Hair et al. (2019b), the general rule is that researchers ought to collect more observations whenever feasible, in general, sample size greater than 100 is preferable. Furthermore, the researchers give the suggestion of 200 and more samples in

multivariate data analysis (Hair et al., 2019b). Consequently, a sample size of 200 is the requirement of minimal sample size from PLS-SEM.

Table 3.1

Recommendations of Minimum Sample Size

Minimum sample size	The requirements
100	1. models containing five or fewer constructs 2. each with more than three items (observed variables) 3. high item communalities (.6 or higher)
150	1. models with seven constructs or less 2. at least modest communalities (.5) 3. no underidentified constructs
300	1. models with seven or fewer constructs, 2. lower communalities (below .45), 3. and/or multiple underidentified (fewer than three) constructs
500	1. models with large numbers of constructs 2. some with lower communalities 3. and/or having fewer than three measured items

Source: Hair et al. (2019b)

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Considering the sample size estimation derived from G*Power software and the requirements for PLS-SEM, this study adopts a minimum sample size of 200. Moreover, Hair et al. (2019b) recommend obtaining a larger sample than necessary to account for potential missing data. Furthermore, Keyton (2022) advocates oversampling in communication research to enhance response rates. Given that some Chinese web dramas included in this study have limited audiences, resulting in insufficient data availability, oversampling is therefore deemed necessary to ensure adequate data collection.

Meanwhile, Fink (2017) provides guidance on oversampling, which involves identifying the minimum sample size and determining the additional sample size required based on this minimum. In addition, Salkind (2022) recommends increasing the sample size by an additional 40 – 50% when employing oversampling. Therefore, based on the previously determined minimum sample size of 200, this study adopts an oversampling range of 40 – 50%, corresponding to an additional 80 – 100 participants, which constitutes the oversampling requirement for this research.

In summary, the initial sample size of 200 is increased by 80 – 100, resulting in a recommended range of 280 – 300 for the current study. To determine a more precise sample size within this range, the total data volume of 863 from the sampled objects is divided by each integer from 280 to 300. The result of dividing 863 by 288 yields 2.9965 (rounded to four decimal places), which is closest to the integer 3. Therefore, 288 is selected as the optimal sample size. In summary, this study requires a sample of 288 Chinese web dramas for subsequent analysis.

3.3.7 Sampling Technique

To proportionally sample the 288 Chinese web dramas from the target population, this study employs probability sampling, which is a term commonly used to describe sampling methods based on probability theory and typically involving random selection mechanisms (Babbie, 2020; Boyle & Schmierbach, 2024; Croucher & Cronn-Mills, 2024). Specifically, stratified sampling and systematic sampling will be

applied as appropriate in this research (Babbie, 2020; Boyle & Schmierbach, 2024; Croucher & Cronn-Mills, 2024).

Stratified sampling is a type of probability sampling that involves classifying the members of the target population into roughly homogeneous strata prior to sampling, while systematic sampling is a form of probability sampling in which every kth unit on a list is selected for inclusion in the sample (Babbie, 2020; Boyle & Schmierbach, 2024; Croucher & Cronn-Mills, 2024). Systematic sampling is considered superior to simple random sampling in certain contexts. Meanwhile, as Babbie (2020) noted, stratified sampling can be implemented in conjunction with simple random, systematic, or cluster sampling to enhance sample representativeness by reducing sampling error. Therefore, it is both feasible and appropriate to employ probability sampling through the integration of stratified and systematic sampling in this study.

Concretely, relying on the Chinese web drama database from the Maoyan app, the sampling frame of this study (see Figure 3.1 above) provides a comprehensive list of Chinese web dramas supported by big data since 2018, categorized by year. Consequently, the present study stratifies the target population into seven homogeneous subsets corresponding to the years 2018 through 2024. Meanwhile, in accordance with the proportion of each homogeneous subset's size within the target population, this study determines the sample size for each subset as a preparatory step for systematic sampling. Consequently, based on the study’s sampling frame and

the required total sample size of 288, the current study conducts stratified sampling to achieve the desired sample sizes and proportions for each homogeneous subset (see Table 3.2 below).

Table 3.2

Sample Size and Proportion of Every Homogeneous Subset

Homogeneous Subset	Population Stratum	Proportion	Sample Size
2018	119	13.79%	40
2019	127	14.72%	42
2020	179	20.74%	60
2021	165	19.12%	55
2022	117	13.56%	39
2023	118	13.67%	39
2024 (As of August 15th)	38	4.4%	13
Total	863	100%	288

Source: Maoyan app

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After stratifying the target population by year, the present study proceeds to conduct systematic sampling within each homogeneous subset. Systematic sampling requires determining the sampling interval for each subset based on its sample size, as different subsets have different sizes (Babbie, 2020; Boyle & Schmierbach, 2024; Croucher & Cronn-Mills, 2024). According to Babbie (2020), the formula for calculating the sampling interval is as follows:

$$\text{sampling interval} = \text{population size} \div \text{sample size}$$

Building on this calculation formula, the sampling interval in every homogeneous subset is 3 (rounded from 2.9965; see Table 3.3 below).

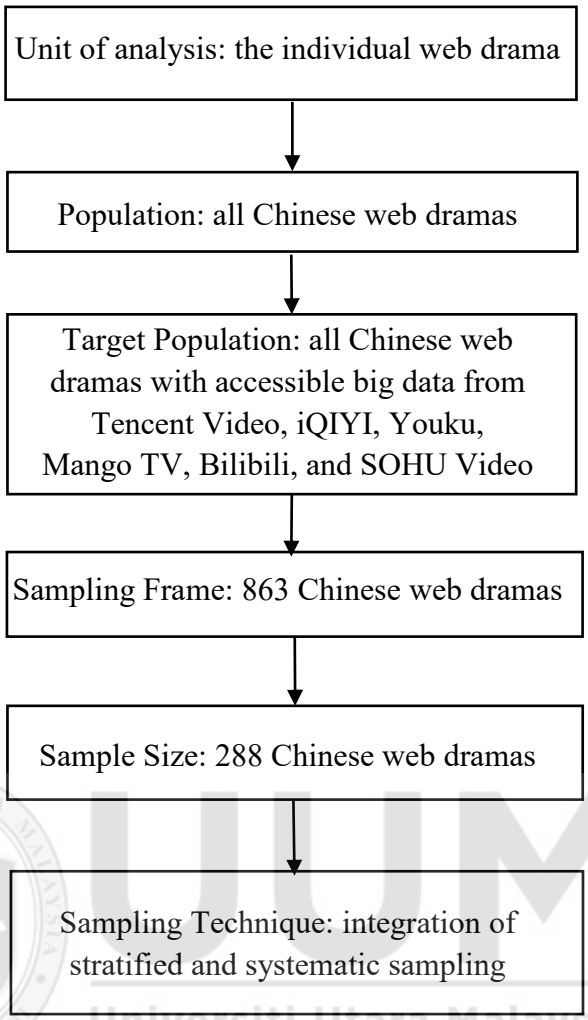
Table 3.3

The Sampling Interval of the Study

3	≈	863	÷	288

Meanwhile, the first sample in each homogeneous subset is selected as a random start, while ensuring compliance with the requirements of systematic sampling (Babbie, 2020; Boyle & Schmierbach, 2024). Ultimately, this study presents the primary components of the research design in Figure 3.3 below.

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Figure 3.3 Primary Components of the Research Design

3.4 Operationalization of the Construct

Operationalization is regarded as the formulation of clear operational definitions or the specification of precise operations employed to measure variables (Babbie, 2020). This section specifies the precise operations used to measure the five constructs of this study. Detailed specifications follow.

3.4.1 Web Drama Audience Satisfaction

The present study treats web drama audience satisfaction as the dependent variable. Measuring it requires integrating big data crawling and sentiment orientation (also known as polarity), a component of sentiment analysis (Liu, 2020; Wankhade et al., 2022). For big data crawling, this study collects data from social media using GooSeeker, a big data acquisition software available on the Internet. Developed by Shenzhen Tianzhu Information Technology Co., Ltd., GooSeeker offers a user-friendly interface and provides researchers with efficient and comprehensive data crawling services (Bao & Hua, 2023; Qiu & Zhang, 2021; Xie et al., 2024). In recent years, an increasing number of communication studies have employed GooSeeker to collect big data from social media (Qiu & Zhang, 2021; Xie et al., 2024; Zhang et al., 2020).

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Meanwhile, this study focuses on the selection of social media platforms. Weibo is China’s largest social media platform (Gan, 2022) and ranks among the most widely used channels for public opinion expression (Wang et al., 2020c; Xu et al., 2022a). Additionally, Douban, China's iconic cultural review and social platform, offers a wealth of well-articulated user commentary on films, TV series, and web dramas (He & Jiao, 2021). As key platforms for information dissemination and user interaction, Weibo (https://weibo.com/) and Douban (https://www.douban.com/) exert significant influence in China (Zhou & Zhao, 2021).

In addition, Zhihu (https://www.zhihu.com/) is the largest web-based knowledge community in China, comparable to Quora, an American online knowledge platform, with 14.7 million users and 830.9 million content items as of the first half of 2024 (Deng et al., 2020; Zhang et al., 2022; Zhihu Inc., 2024). Furthermore, Xiaohongshu (https://www.xiaohongshu.com/explore) is a prominent social media platform known for its high-quality and engaging user-generated content (Chen, 2024) and is often described as China's Instagram (Zhang et al., 2021).

With a growing user base in China and internationally (Wu et al., 2024), Xiaohongshu has surpassed 450 million registered users and over 100 million monthly active users as of August 2020 (Tian et al., 2021). Given these advantages, this study also includes Zhihu and Xiaohongshu as platforms for big data collection. In summary, Weibo, Douban, Zhihu, and Xiaohongshu are the online platforms from which relevant big data are collected using the web crawling software GooSeeker in this empirical study.

Regarding sentiment analysis, this study employs GooSeeker software to measure sentiment orientation. GooSeeker enables researchers to identify positive and negative audience comments on web dramas from social media platforms such as Weibo, Douban, Zhihu, and Xiaohongshu. After collecting large-scale social media comments on web dramas and extracting the volumes of positive and negative comments, the study calculates their respective ratios. These ratios are then used as

indicators of audience satisfaction, with higher values indicating greater satisfaction (Zhou & Zhao, 2021). Specifically, the ratios of positive to negative comment volumes derived from Weibo, Douban, Zhihu, and Xiaohongshu are adopted as the scores for the first four attributes of web drama audience satisfaction.

Moreover, according to Zhou and Zhao (2021), audience ratings from websites such as Douban can reflect audience satisfaction on a specific TV drama. Meanwhile, He and Jiao (2021) note that Douban reviews are a preferred reference for many viewers when deciding what content to consume for entertainment. Furthermore, as stated by Mi et al. (2022), the Douban score reflects viewers' emotional tendencies. Consequently, the Douban score is adopted as one of the attributes of audience satisfaction in this study. By using the name of each web drama as a keyword and searching it in the Douban search box, the researcher obtains the corresponding Douban score, which serves as the value for the final attribute of web drama audience satisfaction.

In summary, web drama audience satisfaction is operationalized as a construct comprising five dimensions: the ratio of positive to negative comment volume on Weibo (coded as AS1), the ratio of positive to negative comment volume on Douban (coded as AS2), the ratio of positive to negative comment volume on Zhihu (coded as AS3), the ratio of positive to negative comment volume on Xiaohongshu (coded

as AS4), and the Douban score for a given web drama (coded as AS5) (see Table 3.4 below).

3.4.2 Web Drama Viewing Motivation

The present study employs web drama viewing motivation as the independent variable. To measure this construct, a combination of big data collection and sentiment analysis techniques, specifically intent mining (Liu, 2020; Wankhade et al., 2022), is utilized. Notably, the previously collected big data, originally gathered to assess web drama audience satisfaction, can be effectively repurposed for this measurement.

Subsequently, in response to the previously collected big data, this study employs intent mining as the analytical approach. Specifically, intent mining uses Python to identify whether each audience comment on web dramas contains expressions of viewing motivation (Liu, 2020). This process enables the quantification of comments expressing such intent, which are then used as values for the attributes of web drama viewing motivation. In this research, Miniconda is utilized to manage and run Python environments (Bercowsky Rama, 2022; Habibie & Nurda, 2024; Pajankar & Joshi, 2022).

In summary, web drama viewing motivation is operationalized as a construct comprising four dimensions: the number of comments expressing viewing intent for

a given web drama on Weibo (coded as VM1), on Douban (coded as VM2), on Zhihu (coded as VM3), and on Xiaohongshu (coded as VM4) (see Table 3.4 below).

3.4.3 Web Drama Exposure

This study adopts web drama exposure as the mediating variable. In measuring web drama exposure, the extent to which audiences actively search for specific information reflects their level of attention and interest, as well as the perceived importance and influence of that information. Therefore, the search volume of a given web drama serves as an indicator of its exposure level (Donovan & Rapp, 2020; Zhou & Zhao, 2021).

With regard to web dramas, audience members who intend to watch a specific title typically begin by searching for it on major search engines such as Baidu in China, before accessing the relevant video platforms to view the content (Zhou & Zhao, 2021). Therefore, the level of web drama exposure can be measured through search volume. Consequently, the search index of a web drama serves as a feasible indicator of its exposure level.

Meanwhile, benefiting from the rapid development of Chinese Internet companies and continuous innovations in Internet technology, researchers can now easily access web show search indices, including the Baidu Search Index

(https://index.baidu.com/v2/index.html) provided by Baidu Inc. and the 360 Trend (https://trends.so.com/) provided by 360 Inc.

The Baidu Search Index, derived from Baidu Inc.'s extensive user behavior data, enables researchers to assess the search volume of specific keywords on Baidu, track their temporal trends, and monitor related news and public opinion dynamics (Fang et al., 2021; Qiu, 2021; Tu et al., 2021; Wang et al., 2020d). It has been widely adopted in research for predicting and analyzing human behavioral patterns (Fang et al., 2021; Qiu, 2021; Tu et al., 2021; Wang et al., 2020d).

Moreover, 360 Inc. is regarded as one of the leading digital platform service providers in China (Wu et al., 2022). 360 Search ranks as the second-largest search engine in the Chinese market after Baidu (Gao et al., 2018). As a big data analytics platform leveraging extensive user data from 360 Inc., 360 Trend aggregates large-scale search, browsing, and social media behavior across the web, enabling researchers to rapidly capture popularity trends and identify users' genuine interests through keyword queries (Gao et al., 2018). Accordingly, this study adopts the Baidu Search Index and 360 Trend data for a specific web drama as two indicators of web drama exposure.

In addition, as a professional big data platform for the media industry, Maoyan (via the Maoyan app) provides the popularity index and exposure volume for specific

web dramas, which can be used to assess web drama exposure (Chou & Lin, 2023; Mi et al., 2022). Therefore, this study incorporates the Maoyan Popularity Index and Maoyan Exposure Volume of a particular web drama as two additional indicators of web drama exposure.

In addition, TikTok has become the world's largest short video platform, characterized by a vast user base and substantial market influence (Zhang et al., 2024). Chinese TikTok maintains close integration with traditional social media platforms, enabling content posted on it to be easily shared across other major social networks (Li & Kang, 2021).

Additionally, Chinese Kwai is recognized as China's second-largest video sharing platform (Li & Cai, 2024). The number of users and the frequency of short video usage have increased annually, driven by the widespread popularity of short video platforms such as TikTok and Kwai (Yan et al., 2023). Both Chinese TikTok and Chinese Kwai provide playback volume data for specific web dramas, making it feasible to incorporate them as two additional indicators of web drama exposure in this study.

To sum up, in this study, web drama exposure is operationalized as a construct encompassing six dimensions: the Baidu Search Index of a given web drama (coded as WDE1), the 360 Trend of a given web drama (coded as WDE2), the Maoyan

Popularity Index of a given web drama (coded as WDE3), the Maoyan exposure volume of a given web drama (coded as WDE4), the playback volume of a given web drama on Chinese TikTok (coded as WDE5), and the playback volume of a given web drama on Chinese Kwai (coded as WDE6) (see Table 3.4 below). By using the name of each web drama as a search keyword and entering it into the search interfaces of Baidu Search Index, 360 Trend, Maoyan, Chinese TikTok, and Chinese Kwai, researchers can obtain the corresponding data.

3.4.4 Web Drama Audience's Social Media Engagement

This study adopts web drama audience's social media engagement as the other mediating variable. With regard to measuring social media engagement, the WeChat Index is a fundamental data tool that uses keywords as analytical cues to help users assess the popularity of specific topics within WeChat based on big data (Lu & Zhang, 2020; Wang et al., 2020b). The index can be accessed through the WeChat app, the most widely used Chinese social media platform (Wang et al., 2020b), which has significantly influenced individuals' interpersonal relationships, communication patterns, and social interactions (Hassan et al., 2021).

Therefore, this study applies the WeChat Index as an indicator of social media engagement. Researchers can obtain the relevant data directly from the WeChat app. Specifically, the search is conducted by entering the name of the web drama on the

Discover page of WeChat. Subsequently, users access the WeChat Index module and click on it, after which the corresponding index value is immediately displayed.

Similar to the WeChat Index, Weibo conversation volume and Weibo interaction volume, which are data metrics provided by the Weibo app, are utilized in this study. Weibo offers diverse channels for interpersonal interaction, enabling Chinese users to communicate and express their thoughts (Wang et al., 2020a). As a result, Weibo has become a crucial online platform and data source for scholars seeking to understand social issues through unobtrusive methods (Li et al., 2020). For example, social interaction data from Weibo can be used to predict audience personality traits (Jiang et al., 2021), and Weibo data is highly valuable in identifying the emotional focus and orientation of the general public through big data analytics (Xu et al., 2022a).

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Accordingly, based on Weibo big data, Weibo conversation volume and Weibo interaction volume are employed as two indicators to measure social media engagement. Specifically, by entering the name of a specific web drama as a keyword into the search box provided by the Weibo app (Zhou & Zhao, 2021), the corresponding results can be readily obtained.

In addition, Tsai and Lin (2023) employ the number of Facebook comments on the American TV show *The Voice* as an indicator of Facebook engagement to investigate

its association with the show's TV performance. Moreover, as previously mentioned, comments on Douban are widely used by viewers as a key reference when making decisions about content consumption and enjoyment (He & Jiao, 2021). Drawing on these studies, this study incorporates the number of brief reviews and the number of comments from Douban for a specific web drama as two indicators of social media engagement. Specifically, after entering the title of a particular web drama as a keyword into the search box on the Douban website, the relevant results can be obtained separately.

To sum up, web drama audience's social media engagement is operationalized as a construct comprising five dimensions: the WeChat Index of a given web drama (coded as SME1), the Weibo conversation volume of a given web drama (coded as SME2), the Weibo interaction volume of a given web drama (coded as SME3), the number of brief reviews for a given web drama on Douban (coded as SME4), and the number of comments for a given web drama on Douban (coded as SME5) (see Table 3.4 below).

3.4.5 Social Media Community Size

This study includes social media community size as a moderating variable. Regarding its measurement, Dolan (2015) measures social media community size using the number of fans on a brand's Facebook page during data collection. Meanwhile, Nepomuceno et al. (2020) assess online community size based on the

total number of fans within an online community. Drawing on Dolan (2015) and Nepomuceno et al. (2020), this study employs the number of fans on the official Weibo account of a given web drama (coded as SMCS1) as the indicator of social media community size (see Table 3.4). In this study, social media community size is operationalized as a unidimensional construct.

Owing to the use of Structural Equation Modeling (SEM) in this study, it is necessary to examine whether the number of indicators for each variable meets the requirements established by scholars for SEM analysis. As Kline (2023) suggested, a safer minimum includes three to five indicators per factor; factors with fewer indicators are more likely to lead to technical issues during model estimation. In this study, each variable has four to six indicators except for the moderating variable. With regard to the moderating variable, Hair et al. (2022) note that moderators can be measured using either a single item or multiple items. This indicates that a single-indicator construct, such as social media community size, is acceptable. Therefore, the number of indicators for each variable in this study satisfies the minimum criteria for SEM analysis.

In addition, it is important to clarify the theoretical foundations from which the aforementioned variables are derived in this study. Two underlying theories support the present research: UGT and CCT. Based on the conceptualization and operationalization of constructs, web drama audience satisfaction, web drama

viewing motivation, web drama exposure, audience social media engagement, and social media community size are grounded in UGT. Meanwhile, web drama exposure, audience social media engagement, and social media community size are also informed by CCT. These constructs are operationalized within the thesis's theoretical framework.

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Table 3.4

Constructs, Attributes, and Corresponding Data Sources

Constructs	Attributes	Data Sources
Web Drama Audience Satisfaction (AS)	The ratio of positive to negative comment volume for a given web drama on Weibo (AS1)	https://weibo.com
	The ratio of positive to negative comment volume for a given web drama on Douban (AS2)	https://www.douban.com
	The ratio of positive to negative comment volume for a given web drama on Zhihu (AS3)	https://www.zhihu.com
	The ratio of positive to negative comment volume for a given web drama on Xiaohongshu (AS4)	https://www.xiaohongshu.com/explore
	Douban score for a given web drama (AS5)	https://www.douban.com
Web Drama Viewing Motivation (VM)	The number of comments expressing viewing intent for a given web drama on Weibo (VM1)	https://weibo.com
	The number of comments expressing viewing intent for a given web drama on Douban (VM2)	https://www.douban.com
	The number of comments expressing viewing intent for a given web drama on Zhihu (VM3)	https://www.zhihu.com
	The number of comments expressing viewing intent for a given web drama on Xiaohongshu (VM4)	https://www.xiaohongshu.com/explore
Web Drama Exposure (WDE)	Baidu Search Index of a given web drama (WDE1)	https://index.baidu.com/v2/index.html
	360 Trend of a given web drama (WDE2)	https://trends.so.com
	Maoyan Popularity Index of a given web drama (WDE3)	Maoyan app
	Maoyan exposure volume of a given web drama (WDE4)	Maoyan app
	Playback volume of a given web drama on Chinese TikTok (WDE5)	Chinese TikTok app
	Playback volume of a given web drama on Chinese Kwai (WDE6)	Chinese Kwai app

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Table 3.4 continued

Constructs	Attributes	Data Sources
Web Drama Audience's Social Media Engagement (SME)	WeChat Index of a given web drama (SME1)	Wechat app
	Weibo conversation volume of a given web drama (SME2)	Weibo app
	Weibo interaction volume of a given web drama (SME3)	Weibo app
	The number of brief reviews for a given web drama on Douban (SME4)	https://www.douban.com
	The number of comments for a given web drama on Douban (SME5)	https://www.douban.com
Social Media Community Size (SMCS)	The number of fans on the official Weibo account of a given web drama (SMCS1)	https://weibo.com

Source: Chou & Lin, 2023; Dolan, 2015; Donovan & Rapp, 2020; Fang et al., 2021; Gao et al., 2018; He & Jiao, 2021; Jiang et al., 2021; Liu, 2020; Li et al., 2020; Lu & Zhang, 2020; Mi et al., 2022; Qiu, 2021; Tu et al., 2021; Tsai & Lin, 2023; Wang et al., 2020b; Wang et al., 2020d; Xu et al., 2022b; Zhao et al., 2019; Zhou & Zhao, 2021; Partial new attributes developed by this study.

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3.5 Data Collection Procedures

After sampling the required cases, the study proceeds to precisely collect data from the sampled web dramas. Using established data collection techniques, this study systematically gathers data for all attributes of each construct.

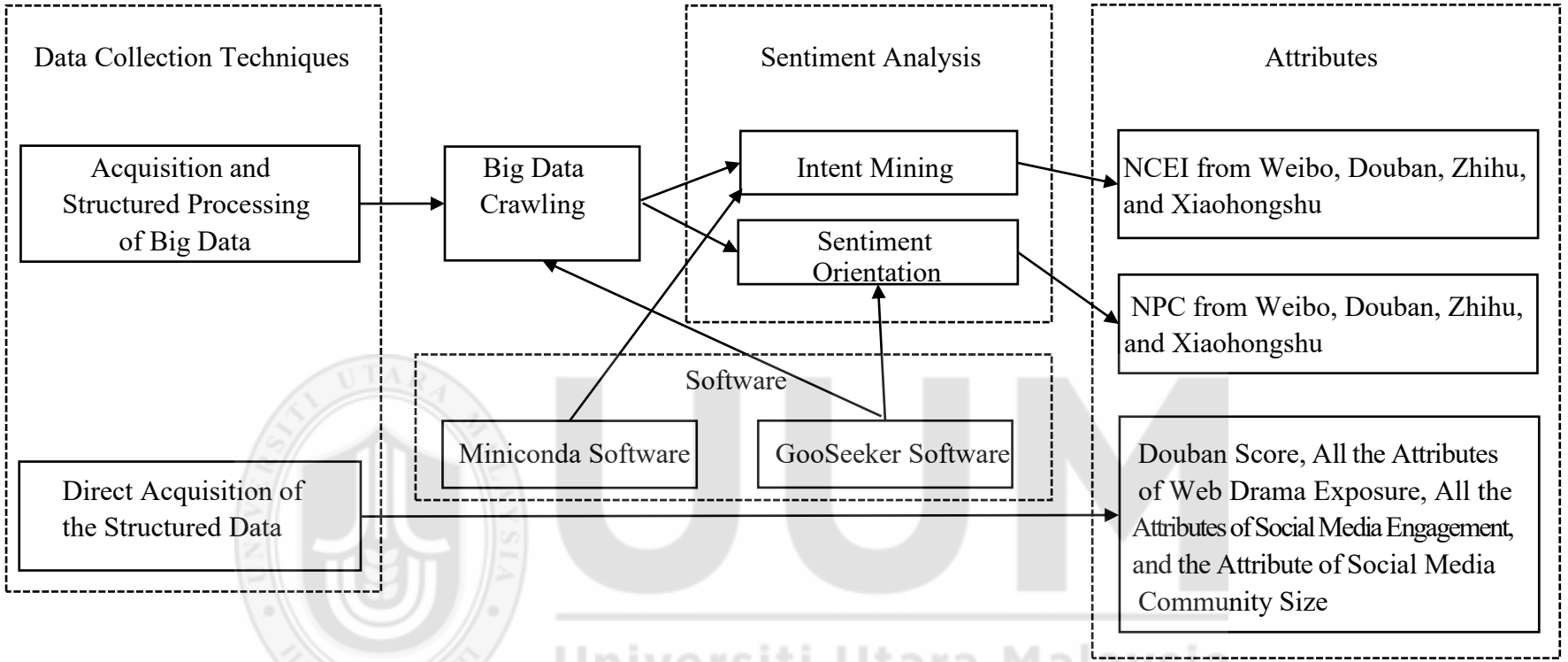
3.5.1 Data Collection Techniques

In accordance with Zhou and Zhao (2021), the big data analytics approach encompasses two data collection techniques in communication research. The first involves researchers using web crawler technology to collect large-scale data from the Internet, followed by structuring the data through sentiment analysis, thereby obtaining structured datasets that can be directly used for statistical analysis. The second involves researchers directly retrieving structured data through searches on major online platforms, where such data are generated through computations enabled by big data technologies (Zhou & Zhao, 2021).

In the first data collection technique, the present study adopts two approaches of sentiment analysis: sentiment orientation and intent mining (Liu, 2020; Wankhade et al., 2022). The former supports the measurement of web drama audience satisfaction, while the latter is used to measure viewing motivation. This study specifies the corresponding attributes for all variables, each requiring specific data collection techniques. Specifically, data collection for the attributes AS1, AS2, AS3, and AS4 of web drama audience satisfaction and for all attributes of viewing motivation

employs the first technique, while the remaining attributes utilize the second technique. Figure 3.4 below illustrates the two big data collection techniques of this study. More details are discussed below.

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Note: NCEI: The number of comments expressing intent for a certain web drama;
RPNCV: The ratio of positive to negative comment volume.

Figure 3.4 The Two Big Data Collection Techniques of the Study

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3.5.2 Procedure

3.5.2.1 Constructs, Attributes, and Corresponding Data Sources

To clarify the data collection procedure of this study, it is necessary to summarize and present all constructs, their attributes and their data sources, which are comprehensively provided in Table 3.4 above.

3.5.2.2 Level of Measurement

There are four levels of measurement in social research, comprising nominal, ordinal, interval, and ratio measure (Babbie, 2020; Boyle & Schmierbach, 2024; Croucher & Cronn-Mills, 2024). Ratio measure is considered as a measurement level that describes a variable which is based on a true zero point and has all the characteristics of nominal, ordinal, and interval measures (Babbie, 2020; Boyle & Schmierbach, 2024; Croucher & Cronn-Mills, 2024). All the variables of this study are consistent with the definition and characteristic of ratio measure, consequently, the level of measurement is ratio measure in the present study.

3.5.2.3 Data Collection Procedure for All Attributes of Web Drama Audience Satisfaction

First and foremost, this study employs the crawler software GooSeeker to collect comments on a specific web drama from Weibo, Douban, Zhihu, and Xiaohongshu. The big data crawling process using GooSeeker consists of six steps, as follows: First, researchers launch the GooSeeker software and determine which website and

webpage to crawl for data collection. For example, Appendix A illustrates the first step using Douban as a case.

After selecting the specific webpage on Douban, the researchers proceed to the second step, illustrated in Appendix B: registering and logging in to Douban. Incomplete data crawling may occur if registration and login are not completed. Once registration and login have been successfully completed, the researchers move to the third step, shown in Appendix C, which involves entering the title of the target web drama into Douban's search box to retrieve relevant comments.

After reviewing the relevant comments of the web drama on Douban, the researchers copied the webpage link and pasted it into the designated field in the GooSeeker software. Upon completing this step, clicking the "data acquisition" button initiated the automated crawling of big data from Douban. An illustration of this procedure is provided in Appendix D.

In summary, the first four processes described above serve as preparatory steps for big data crawling using the GooSeeker software. Subsequently, the fifth process involves the automated execution of data crawling by the GooSeeker software, as illustrated in Appendix E. Upon completion of this crawling phase, the software stores all collected data and grants researchers access to retrieve it. At this stage, the

researchers can download the data into an Excel document. The final step in this workflow is outlined in Appendix F.

After obtaining the big data from GooSeeker in electronic format, the researchers used GooSeeker software to measure sentiment orientation (Liu, 2020; Wankhade et al., 2022). The software incorporates a built-in sentiment analysis function, as shown in Appendix G. To utilize this feature, researchers input a task name and import the relevant data file, enabling the system to classify crawled comments into positive, negative, and neutral categories and compute their respective counts, as illustrated in Appendix H. The resulting classification output is presented in Appendix I. Subsequently, by dividing the number of positive comments by the number of negative comments, the researchers calculated the positive-to-negative comment ratio, which corresponds to the values of AS1, AS2, AS3, and AS4. The corresponding flowchart is displayed in Figure 3.5 below.

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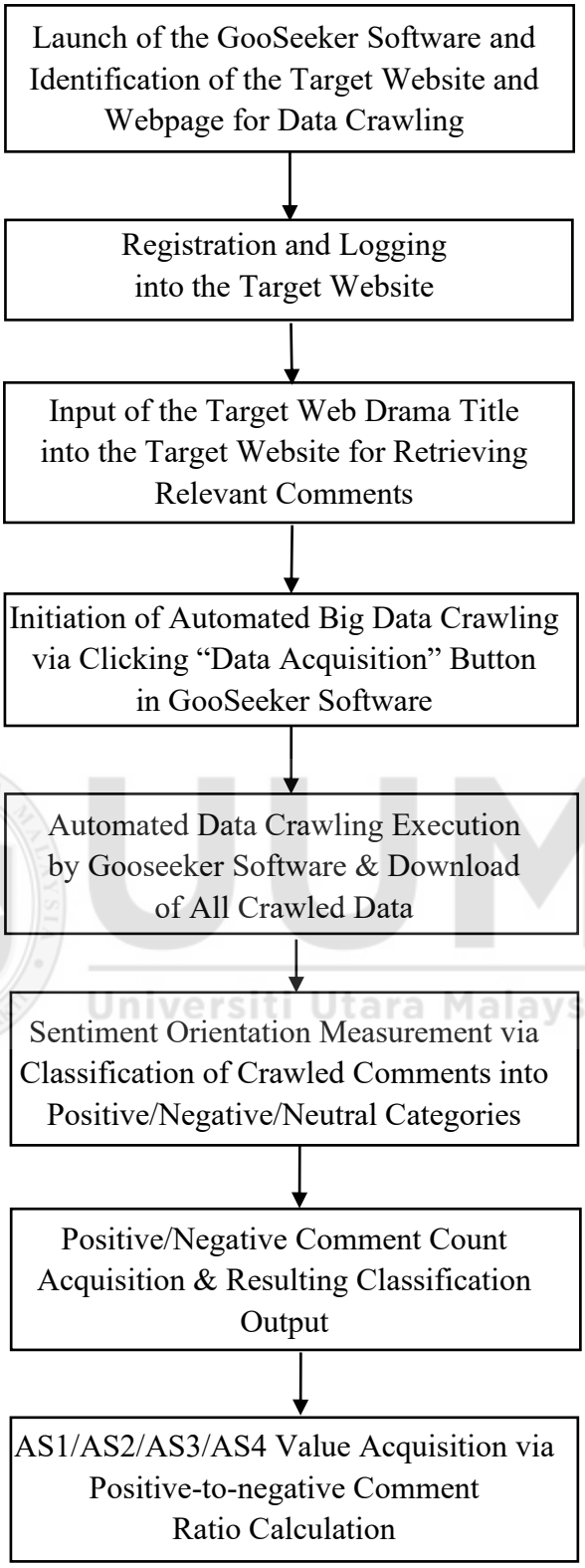


Figure 3.5 Flowchart of Data Collection Procedure for AS1/AS2/AS3/AS4

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Moreover, the Douban score is adopted as the final attribute of web drama audience satisfaction in this study. By using the web drama's title as a keyword and entering it into the Douban search box, the researcher can retrieve the resulting data, thus obtaining the values of AS5 (see Figure 3.6 below and Appendix J).

3.5.2.4 Data Collection Procedure for All Attributes of Web Drama Viewing Motivation

Similar to the measurement of web drama audience satisfaction, the data acquisition for all viewing motivation attributes is designed to integrate big data collection with sentiment orientation measurement, an application of sentiment analysis (Liu, 2020; Wankhade et al., 2022). Specifically, the measurement involves two steps. First, researchers use GooSeeker software to crawl comments on a specific web drama from Weibo, Douban, Zhihu, and Xiaohongshu, a procedure consistent with the one used for measuring audience satisfaction attributes. Consequently, the same set of crawled comments can be utilized for both measurements.

Following this, the present study aims to apply intent mining, which is regarded as a subfield of sentiment analysis (Liu, 2020; Wankhade et al., 2022), to analyze large-scale social media data. The goal of this analysis is to identify and quantify comments that express viewing motivations toward a given web drama. As a prominent and challenging area within NLP, sentiment analysis enables the classification of textual content at the sentence level, thereby supporting the accurate

measurement of user intent in online discourse (Wankhade et al., 2022; Xu et al., 2022b).

Furthermore, deep learning, which is based on artificial neural networks and particularly effective in processing text, image, video, speech, and audio data, will be applied to the task of sentiment analysis (Janiesch et al., 2021). To advance this approach, the study employs convolutional neural networks (CNN), a type of deep learning model (Taye, 2023), to conduct intent mining (Janiesch et al., 2021), supported by recent applications in similar domains (Castellani & Rajaram, 2021; Habib & Qureshi, 2022).

Meanwhile, this study leverages Python, a high-level, general-purpose programming language developed in the late 1980s, to support intent mining (Taori & Dasararaju, 2019). This choice is informed by Python's widespread adoption and rapid growth in scientific computing and data analytics applications (Taori & Dasararaju, 2019). As noted by Taori and Dasararaju (2019), Python is applicable to a broad range of computational tasks, including web scraping, data collection, data cleaning and manipulation, web development, statistical analysis, and machine learning. To ensure smooth execution of Python, this study employs Miniconda, a software platform designed for the installation, management, and operation of Python environments (Bercowsky Rama, 2022; Habibie & Nurda, 2024; Pajankar & Joshi, 2022).

Following the construction of the convolutional neural network model, this study employs over 3,000 comments expressing intentions related to entertainment, relaxation, escapism, passing time, information seeking, or social interaction to train and test the model, as these represent the primary motivations for viewing web dramas (Hu, 2021; Wang, 2022). These comments were identified by researchers.

After all preparations have been completed, the present study successfully conducts intent mining using Python. Specifically, the procedure is as follows: First, the researcher should copy all comments collected by the GooSeeker software and paste them into a designated "test" file, which serves as a repository for the data. It is important to note that each line must correspond to a single comment to ensure accurate identification. Appendix K illustrates this process using the web drama *The Longest Day in Chang'an* as an example.

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Moreover, the researcher runs Python within the Miniconda environment by inputting relevant commands, as illustrated in Appendix L. Upon receiving these instructions, Python rapidly analyzes each comment to identify those reflecting viewers' motivations for watching web dramas, such as entertainment, relaxation, escapism, passing time, information seeking, or social interaction. These identified comments are then displayed in real time. Simultaneously, the total number of intent-expressing comments is calculated for quantitative assessment. The output, presented in Appendix M, represents the number of comments expressing viewing

intentions toward a specific web drama that were collected from social media. The flowchart illustrating the process is shown in Figure 3.6 below.

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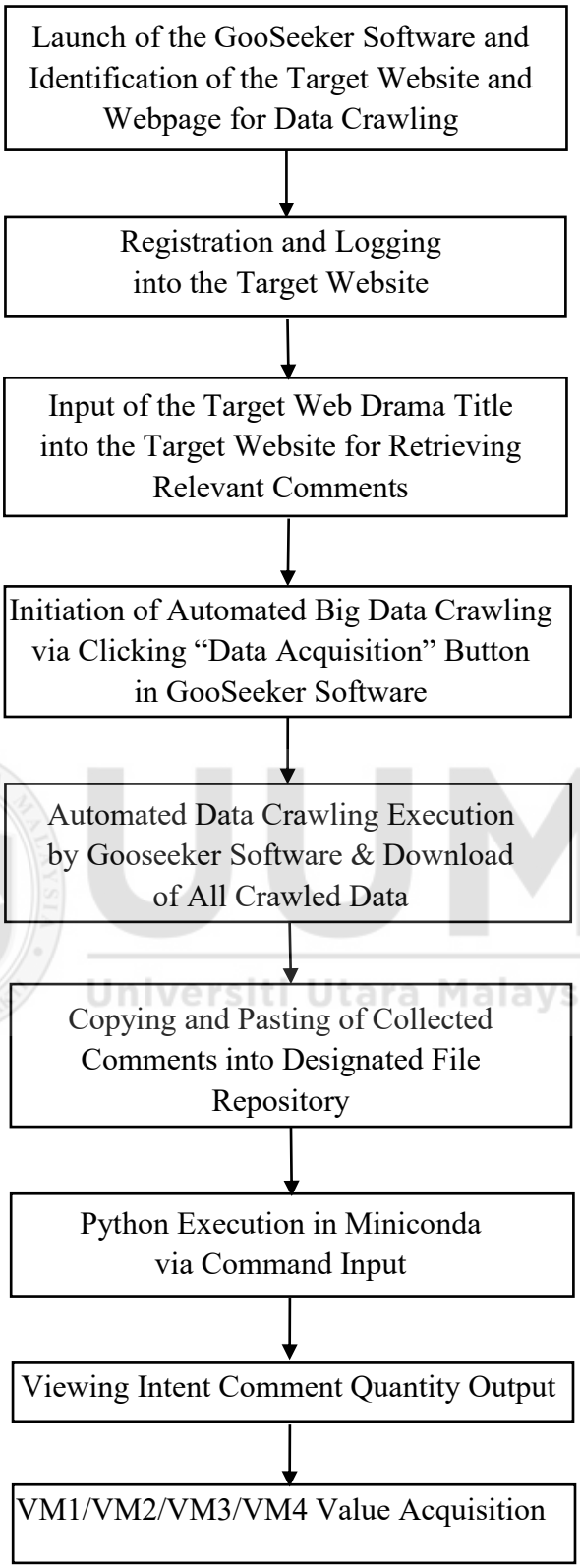


Figure 3.6 Flowchart of Data Collection Procedure for VM1/VM2/VM3/VM4

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In addition, the accuracy rate of this convolutional neural network model must be evaluated in the present study. To this end, the Chinese web drama *The Longest Day in Chang'an* is selected as a case study to assess the accuracy of intent mining using Python. The results are as follows: 8,516 related comments posted on Weibo between 27 May 2019 and 27 June 2019 were collected, among which the intent mining process identified 1,015 comments expressing viewing intent. However, manual review by the researcher revealed that the actual number of genuine intent-expressing comments is 931.

Therefore, the accuracy rate is approximately 91.72%. The lack of perfect accuracy may be attributed to the complexity of linguistic expression in conveying emotions, which can lead to misclassification by the system; such errors cannot be entirely avoided. In the absence of established benchmarks in the existing literature regarding acceptable accuracy rates for intent mining, this study considers the achieved accuracy sufficient to justify the use of this convolutional neural network model for intent mining in the current research.

In addition, careful attention should be paid to the distinction between comments expressing viewing intent and those that are merely positive or negative in sentiment. Drawing on UGT, the needs that give rise to expectations from mass media or other information sources lead to differential exposure to or engagement in specific media activities, which in turn result in need gratification and associated outcomes

(McQuail & Deuze, 2020; Katz et al., 1974; West & Turner, 2020). Meanwhile, audience satisfaction is equivalent to the gratification experienced following media exposure (Bae, 2018; Perse & Ferguson, 2000). This indicates that motivational drivers precede audience satisfaction in the process of media consumption.

In this study, comments expressing viewing intent are used to measure audience motivation, while positive and negative comments are employed to assess audience satisfaction. Consequently, the emergence of intent-expressing comments precedes that of positive and negative comments. Moreover, this temporal pattern is further supported by empirical observation: intent-related comments typically appear before and during the release of a web drama, whereas positive and negative evaluations predominantly emerge during and after its release.

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3.5.2.5 Data Collection Procedure for All Attributes of the Other Three Variables

As previously mentioned, the data collection procedure for all attributes of the other three variables involves researchers directly obtaining structured data through searches on major online platforms. These structured data are generated through big data computations using specific algorithms, facilitated by big data technologies.

Specifically, the values of the other twelve attributes are obtained by using the web drama's title as a keyword and entering it into the corresponding search box, allowing

the researcher to retrieve the relevant data. The relevant search results, including the Baidu Search Index, 360 Trend, Maoyan Popularity Index, Maoyan Exposure Volume, TikTok playback volume, Kwai playback volume, WeChat Index, Weibo conversation volume, Weibo interaction volume, number of brief reviews on Douban, number of comments on Douban, and number of fans on the official Weibo account of a specific web drama, are presented in Appendices N through Y. The related flowchart is presented in Figure 3.7 below.

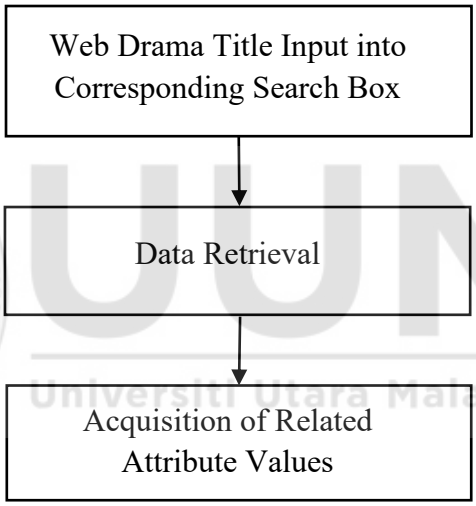


Figure 3.7 Flowchart of Data Collection Procedure for AS5 and All Attributes of the Other Three Variables

3.6 Statistical Analysis Procedures

After collecting all the data in accordance with the data collection procedures, this study proceeds to conduct statistical analysis. This section includes data analysis preparation, assessment of underlying statistical assumptions, and descriptive analysis, detailing the steps taken to prepare the data and the conditions that must be satisfied before analysis can be conducted. The statistical analysis procedures in this

study are carried out with the support of two distinct software packages: Statistical Package for the Social Sciences (SPSS) 29.0 and SmartPLS 4.1.

First and foremost, SPSS is employed to facilitate several critical processes, including data analysis preparation and the assessment of underlying statistical assumptions. At the same time, this study uses SPSS to conduct descriptive analysis, enabling a preliminary discussion of the phenomena reflected in the data and providing an initial understanding. Subsequently, SmartPLS 4.1 is adopted to assess the measurement model and perform hypothesis testing (Cheah et al., 2023c; Hair et al., 2022; Hair et al., 2024).

Hair et al. (2011) and Sarstedt et al. (2023) conclude that partial least squares–structural equation modeling (PLS-SEM), when appropriately applied, is a robust and effective approach for estimating models in various theoretical frameworks and empirical data contexts. This study aims to develop a predictive model; therefore, PLS-SEM is employed. The following section provides a more detailed account of the procedures.

3.6.1 Preparation for Data Analysis

Once structured data are successfully extracted from big data through sentiment analysis, they can be transferred into an Excel spreadsheet and subsequently imported into SPSS. The data preparation phase focuses on cleaning and refining the

dataset by addressing five common issues in raw data: monotonicity assessment, applying logarithmic transformation, managing missing data and outlier, and performing data normalization (Baydoğmuş, 2021; Baddoo et al., 2021; Elkhouly et al., 2023; Hair et al., 2019b; Henderi et al., 2021; Kwak & Kim, 2017; Mirzaei et al., 2022; Noel, 2021; Roni & Djajadikerta, 2021; Smiti, 2020; Tabachnick, 2019). Data analysis will be conducted using SPSS version 29.0 in this study.

Monotonicity refers to responses that exhibit insufficient or no variation, which are characterized by repetitive or uniform patterns (Roni & Djajadikerta, 2021). Such data points carry minimal or negligible analytical value and may therefore be excluded from analysis, provided their removal is properly documented in the research report (Roni & Djajadikerta, 2021; Stieglitz et al., 2018). Visual inspection can be an effective method for identifying monotonic responses when the sample size is small (Roni & Djajadikerta, 2021). However, given that big data typically contain high variability and strong empirical credibility, the likelihood of encountering monotonicity in this study is very low.

Regarding logarithmic transformation, in multivariate data analysis, this technique effectively addresses potentially undesirable characteristics of variables (Boyle & Schmierbach, 2024; Curran-Everett, 2018; Hair et al., 2019b). Large-scale data span multiple orders of magnitude, which may result in severe non-normality and undermine model robustness (Wooldridge, 2021). By applying logarithmic

transformation to big data, this study effectively reduces the scale of the data, thereby enhancing symmetry in data distribution and improving the robustness of statistical inference. Meanwhile, prior studies on big data have employed logarithmic transformation to facilitate more effective data analysis (Alevizos et al., 2025; Shachar et al., 2018). Therefore, the current study applies logarithmic transformation, which was performed using SPSS 29.0.

With regard to missing data, it refers to data that are unavailable in a specific context (Clark et al., 2022; Tabachnick, 2019), posing a significant challenge in social science research (Ochieng' Odhiambo, 2020; Tabachnick, 2019). There are several reasons for the emergence of missing data; for instance, participants may omit questions in survey research, or provide invalid responses (Mirzaei et al., 2022; Roni & Djajadikerta, 2021; Tabachnick, 2019).

Given that the target population of this study includes all Chinese web dramas with accessible big data from six major video platforms, the likelihood of encountering missing data is extremely low. Unless there is a network malfunction that prevents researchers from accessing the data, such an occurrence is unlikely. Nevertheless, when conducting quantitative research, researchers ought to address how to handle the issue of missing data (Clark et al., 2022; Tabachnick, 2019).

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Confronted with the challenges of missing data, initially, in circumstances where the amount of missing data is minimal, researchers have the option to omit them (Babbie, 2020; Tabachnick, 2019). However, it is advisable to avoid this approach, as bias may be introduced if the excluded samples differ from those included (Mirzaei et al., 2022; Roni & Djajadikerta, 2021).

Moreover, apart from deletion, Roni and Djajadikerta (2021) introduce three alternative approaches for handling missing values: mean substitution, multiple imputation, and expectation maximization. In addition, the two scholars recommend adopting the latter two methods because they are more accurate. The present study follows these recommendations by applying expectation maximization to address missing values using SPSS. More importantly, researchers are required to examine the percentage of missing data for each variable; if it exceeds 20%, which is considered the upper threshold for acceptable missingness, the results may become biased as a consequence (Roni & Djajadikerta, 2021).

In terms of outliers, they refer to data points that are substantially distant from the main cluster (Roni & Djajadikerta, 2021; Tabachnick, 2019). In big data research, outliers must be appropriately managed during the data cleaning and preprocessing stages to ensure accurate insights are obtained (Ridzuan & Zainon, 2022). With the aid of SPSS, researchers can identify the presence of outliers in sample data using scatterplots, boxplots, or Q-Q plots (Kline, 2023; Roni & Djajadikerta, 2021). The

present study employs the boxplot method to detect outliers (Kline, 2023; Roni & Djajadikerta, 2021; Tukey, 1977). After identification, this study seeks to minimize their impact by transforming outlier values into those corresponding to the nearest non-extreme scores (Kline, 2023; Kwak & Kim, 2017; Roni & Djajadikerta, 2021).

Regarding data normalization, it is a practical approach for integrating data from various sources onto a common scale (Han et al., 2019; Noel, 2021). Given that attribute values are measured on different units and cannot be directly compared or computed, this study employs data normalization as the data processing method. Specifically, Z-score normalization, a method frequently employed by researchers, transforms original data into new values with a mean of zero and a standard deviation of one, enabling valid comparisons and calculations across indicators measured on different scales (Elkhouly et al., 2023; Henderi et al., 2021; Han et al., 2019; Noel, 2021). Therefore, this study adopts Z-score normalization to perform data normalization on the sample data using SPSS 29.0.

3.6.2 Underlying Statistical Assumptions

The test of underlying statistical assumptions is part of the preliminary analysis in this study. Multivariate techniques can only be applied appropriately when a set of basic assumptions consistent with the requirements of statistical theory are met (Hair et al., 2019b). Four key statistical assumptions are considered: normality, linearity,

homoscedasticity, and independence of errors (Hair et al., 2019b; Roni & Djajadikerta, 2021; Tabachnick, 2019).

However, Hair et al. (2011) and Hair et al. (2022) argue that, unlike CB-SEM, which relies on a maximum likelihood estimator requiring normally distributed data, PLS-SEM is free from distributional assumptions as it is a non-parametric statistical technique. At the same time, Hair et al. (2022) caution researchers that sample data should not deviate substantially from normality, as severely non-normal data can complicate the assessment of parameter significance; in particular, extreme non-normality may lead to errors such as false negatives. Consequently, the absence of severe non-normality is adopted as one of the underlying statistical assumptions in place of the strict normality assumption in the present study. These assumptions are discussed below.

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3.6.2.1 Absence of Severe Non-normality

Normality that is defined as the shape of the data distribution for an individual metric variable and its connection to the normal distribution is the most basic assumption in multivariate analysis. All of the statistical tests that follow are deemed invalid if the deviation from the normal distribution is significant enough (Hair et al., 2019b; Tabachnick, 2019). Although this issue is significantly less serious when PLS-SEM is embraced to undertake the statistical analysis (Hair et al., 2011; Hair et al., 2022),

the researcher is supposed to implement the examination of the absence of severe non-normality (Hair et al., 2022).

With regard to the measurement, the test of normality can utilize Kolmogorov-Smirnov and Shapiro-Wilk owing to its objectivity (Roni & Djajadikerta, 2021). Supposing that these tests indicate that *p* values of the two are more than 0.05, the investigator can achieve the finding that the sample data follow a normal distribution (Roni & Djajadikerta, 2021). However, according to Hair et al. (2022) and Sarstedt and Mooi (2019), these tests solely determine whether to reject the null hypothesis of normal distribution, lacking of the insight into the extent of deviation from normality. Consequently, it is not appropriate to adopt these tests in determining whether there is the absence of severe non-normality in the present study.

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Instead of Kolmogorov-Smirnov and Shapiro-Wilk tests in multivariate analysis, Hair et al. (2022) make the recommendation that the researcher ought to apply skewness and kurtosis tests for the purpose of verifying whether there is the existence of serious non-normality. Skewness describing the balance of the distribution are two measures that can be used to characterize the shape of any distribution, a higher proportion of smaller values is indicated by a positive skewness, whereas a lower proportion of bigger values is indicated by a negative skewness

(Hair et al., 2019b; Hair et al., 2022; Kim, 2013; Kline, 2023; Orcan, 2020; Tabachnick, 2019).

In addition, kurtosis describing how "peaked" or "flat" the distribution is in relation to the normal distribution, that the kurtosis value being positive indicates that the distribution is more peaked than normal, on the other hand, a negative kurtosis value means that the shape is flatter than normal (Hair et al., 2019b; Hair et al., 2022; Kim, 2013; Kline, 2023; Orcan, 2020; Tabachnick, 2019). As a result, the present study embraces the tests of kurtosis and skewness with SPSS 29.0 for validating the absence of severe non-normality.

3.6.2.2 Linearity

As stated by Hair et al. (2019b) and Tabachnick (2019), the assumption of linearity is implicit in all multivariate techniques that rely on correlational measures of association, such as structural equation modeling. The most popular approaches to identify linearity relationship is to check scatter-plots of the variables (Hair et al., 2019b; Tabachnick, 2019). Consequently, this research attempts to implement the linearity assumption test by means of the scatter-plots (Hair et al., 2019b; Roni & Djajadikerta, 2021; Tabachnick, 2019).

3.6.2.3 Homoscedasticity

The definition of homoscedasticity is the postulation which dependent variable(s) exhibit equal levels of variance across the range of predictor variable(s) (Hair et al., 2019b; Tabachnick, 2019). Similar to normality, both statistical and graphical tests are available to be engaged in the test for homoscedasticity (Hair et al., 2019b; Roni & Djajadikerta, 2021; Tabachnick, 2019). Concretely, the present study attempts to applies scatter-plot to undertake this test (Hair et al., 2019b; Roni & Djajadikerta, 2021; Tabachnick, 2019).

3.6.2.4 Independence of Error

The independence of error makes the requirement that the error of one observation should not be correlated with the error of another observation (Hair et al., 2019b; Tabachnick, 2019). Referring to Hair et al. (2019b), the procedure of data collection is responsible for the violation of the assumption that errors are uncorrelated, meanwhile, the time series data also usually lead to the emergence of correlated errors. Therefore, the independence of error is supposed to be identified and fixed, or the results may contain significant biases (Hair et al., 2019b). The present research intends to adopt Durbin-Watson approach to test it under the assistance of SPSS (Tabachnick, 2019).

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3.6.3 Descriptive Analysis

Descriptive statistics refers to the statistical methods used to summarize and describe the characteristics of a sample or the relationships among its variables; it provides only a summary of a set of observed sample data (Babbie, 2020; Croucher & Cronn-Mills, 2024). The primary purpose of descriptive analysis is to present a clear and concise overview of a dataset, making the variables easier to understand and interpret (Bougie & Sekaran, 2019; Boyle & Schmierbach, 2024; Mishra et al., 2019).

Mishra et al. (2019) identify three principal categories of descriptive statistics: frequency measures (e.g., frequency, percentage), measures of central tendency (e.g., mean, median, mode), and measures of dispersion or variation (e.g., variance, standard deviation, standard error, coefficient of variation, interquartile range, percentiles, range, and quartiles). The present study employs descriptive analysis based on these three primary categories.

3.7 Application of Partial Least Squares-Structural Equation Model (PLS-SEM)

As Kline (2023) introduced, structural equation modeling (SEM) is a set of statistical techniques for estimating the magnitudes and directions of presumed causal effects in quantitative research building on cross-sectional, longitudinal, experimental, or other aspects of research designs. The advantages of SEM are comprised of the ability to analyze causal models prior to data collection, as well as the capacity to differentiate

between latent and observable variables and to test a wide range of hypotheses about measurement and causation, therefore, the researchers are employing SEM at an increasing rate (Kline, 2023). Considering that, SEM is considered as the dominant multivariate technique nowadays (Hair et al., 2019b). In addition, more of the measured variables utilized in SEM are derived from digital big data, such as social media (Hair et al., 2019b). Consequently, the present study embraces SEM.

To go a step further, Hair et al. (2019b) and Latan et al. (2023) make the introduction of PLS-SEM which refers to a variance-based approach for the purpose of estimating structural equation models using total variance and focusing on maximizing the explained variance of the endogenous latent variable(s). There are a lot of advantages of PLS-SEM, such as that PLS-SEM is effective on handling complex models and small sample size, it can process both formative and reflective measurement models, and it possesses higher statistical capability in comparison to CB-SEM (Hair et al., 2019b; Hair et al., 2022; Hair et al., 2024; Latan et al., 2023). As a consequence, it is applicable to a broad range of research situations (Evermann & Rönkkö, 2023; Hair et al., 2022; Hair et al., 2024; Latan et al., 2023).

Owing to that, the application of PLS-SEM has increased dramatically over the last years, attracting a rapidly growing number of scholars (Evermann & Rönkkö, 2023; Hair et al., 2022; Hair et al., 2024; Latan et al., 2023). Besides that, SmartPLS 4.1 is the latest version of the most popular PLS-SEM software (Cheah et al., 2023c; Hair

et al., 2024). Considering that, this study intends to test the eleven hypotheses using PLS-SEM under the assistance of SmartPLS 4.1.

3.8 Confirmatory Composite Analysis (CCA) and the Measurement Model

As claimed by Hair et al. (2019b) and Hair et al. (2022), there are two processes of executing PLS-SEM. Above all, the researchers are supposed to examine and confirm the measurement model by executing CCA (Hair et al., 2019b; Hair et al., 2022). Once the measurement model is reliable and valid based on the results, the researchers can proceed with the second step, that is, to assess the structural model (Hair et al., 2019b; Hair et al., 2022). This part discusses the first process.

The procedure of confirming measurement models with PLS-SEM is characterized as CCA (Hair et al., 2019b; Hair et al., 2020; Hubona et al., 2021). On the basis of the explanations from Hair et al. (2020), compared with confirmatory factor analysis (CFA) and exploratory factor analysis (EFA), CCA is a recently proposed substitute method when utilizing PLS-SEM, providing numerous benefits for validating the measurement models made up of linear composites.

In comparison to CFA, CCA possesses the advantages as follows: the improvement of construct validity, the available determinant construct scores, the application of formative measurement models, being more suitable for prediction as the statistical objective (Hair et al., 2020). In contrast to EFA, CCA is able to supply a more

comprehensive view of measurement properties and can detect a broader spectrum of measurement issues when evaluating the suitability of measurements (Hair et al., 2020). Besides that, it can promote the evaluation of both formative and reflective measuring models (Hair et al., 2020). As a conclusion, CCA had been widely utilized in social science research in recent years (Abbasi, 2022; Pasca et al., 2022; Schamberger et al., 2023).

Furthermore, Hair et al. (2022) provide the CCA procedure which is manifested below: First and foremost, it is necessary to distinguish the reflective measurement model and formative measurement model due to that there are differential assessment steps, followed by that, the researcher undertakes the assessment of measurement model based on the appropriate assessment steps, the more details will be discussed in the next section.

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In accordance with Hair et al. (2022), measurement models are typically classified into two categories: reflective and formative. In the reflective measurement model, a change in the construct leads to a simultaneous change in all its indicators; in other words, the indicators are highly correlated. In contrast, in the formative measurement model, the construct is formed by the set of indicators, and the selected formative indicators must collectively represent the principal elements of the domain. Furthermore, Hair et al. (2022) emphasize that researchers must distinguish between

reflectively and formatively measured constructs prior to assessing the measurement models, as they are grounded in different conceptual foundations.

The measurement model for this study is established based on the five constructs and their respective attributes, which are summarized in Table 3.4 above. After examining the relationships between the five constructs and their corresponding indicators, the study identifies a reflective measurement model. In summary, the present study assesses the measurement model with the assistance of CCA.

3.9 Assessment of the Measurement Model

As has been mentioned above, the measurement model of this study is reflective measurement model. Relying on the statements from Hair et al. (2022), there are four processes for evaluation of the reflective measurement model, namely, indicator reliability, internal consistency reliability, convergent validity, discriminant validity. They are explained below.

3.9.1 Indicator Reliability

Indicator reliability refers to the size of the outer loading (Hair et al., 2022). Testing the indicators' outer loadings is the initial step in the reflective measurement model assessment process, the standardized outer loadings ought to be 0.708 or higher according to a common rule of thumb (Hair et al., 2022). Many previous empirical studies had undertaken the assessment of indicator reliability with the test of the

outer loading (Dolinting & Pang, 2022; Haji-Othman & Yusuff, 2022; Mohd Dzin & Lay, 2021). The outer loadings of all the indicators will be investigated in the present research in the intention of examining the indicator reliability.

3.9.2 Internal Consistency Reliability

Hair et al. (2022) provide the three measures, including Cronbach's alpha, composite reliability and reliability coefficient. Cronbach's alpha is regarded as the conventional criterion for measuring internal consistency reliability (Hair et al., 2019a; Hair et al., 2022). Cronbach's alpha ranges from 0 to 1 and its higher values imply higher reliability levels, while it can be acceptable that its value is more than 0.6 (Hair et al., 2022). The prior empirical investigations evaluated internal consistency reliability of sample data by the examination of Cronbach's alpha (Amirrudin et al., 2020; Francis & Village, 2022; Kalkbrenner, 2021). The present study intends to apply Cronbach's alpha to evaluate internal consistency reliability.

3.9.3 Convergent Validity

Convergent validity refers to the level to which a measure correlates positively with alternative measures of the same construct, the average variance extracted (AVE) is a frequently utilized metric to measure convergent validity and every reflectively measured construct's AVE size ought to be assessed (Hair et al., 2022). building on the established rule of thumb, the AVE value ought to be equal to 0.50 or higher due to that the construct is supposed to explain more than half of the variance of its

indicators (Hair et al., 2022). In empirical studies, the researchers examined the convergent validity though the analysis of AVE (Cheung et al., 2023; Purwanto et al., 2021; Purwanto & Sudargini, 2021; Sujati & Akhyar, 2020). The present study adopts AVE to assess the convergent validity.

3.9.4 Discriminant Validity

Hair et al. (2022) define discriminant validity as the level to which a construct is actually differential from other constructs by empirical standards. The purpose of testing discriminant validity is to make sure that a construct is the only one of its kind in the model (Hair et al., 2022). Hair et al. (2022) offer three approaches, comprising Fornell-Larcker criterion, cross-loadings, and heterotrait-monotrait ratio (HTMT), to measure the discriminant validity. Meanwhile, Henseler et al. (2015) and Hair et al. (2022) make the recommendation that the researchers apply the HTMT criterion to evaluate discriminant validity in PLS-SEM.

Besides that, the HTMT value below 0.9 indicates that the discriminant validity is adequate for conceptually similar constructs, while the HTMT value below 0.85 for conceptually different constructs in the measurement model (Henseler et al., 2015; Hair et al., 2022). Confronted with the test of discriminant validity, some researchers had embraced the HTMT measure smoothly (Afthanorhan et al., 2021; Kamis et al., 2021; Yusoff et al., 2020). Consequently, The present study attempts to follow the

suggestion from Henseler et al. (2015) and Hair et al. (2022) to assess the discriminant validity with HTMT.

3.10 Hypothesis Testing Using Structural Equation Model

3.10.1 Assessment of the Structural Model

As previously mentioned, once the measurement model has been confirmed as reliable and valid, researchers can proceed to the second step: assessing the structural model (Hair et al., 2019b; Hair et al., 2022). Hair et al. (2022) outline specific procedures for evaluating structural model results, including the assessment of potential collinearity issues, the evaluation of the significance and relevance of path relationships, the examination of the model's explanatory power, the assessment of its predictive power, and, where applicable, model comparisons.

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Model comparisons are not required in the present investigation, consequently, the first four processes will be discussed in detail below. In addition, the goodness-of-fit index (GoF) is not used to validate the model in this study, as Henseler and Sarstedt (2012) demonstrate that GoF is unsuitable for model validation, and Hair et al. (2022) recommend that researchers avoid using this measure in PLS-SEM.

3.10.1.1 Assessment of the Structural Model for Potential Collinearity Issues

According to Hair et al. (2022) and Latan et al. (2023), to assess potential collinearity issues, researchers should examine each set of predictors in the structural model.

Specifically, if the Variance Inflation Factor (VIF) value for each predictor is less than 5, and ideally below 3, collinearity does not substantially affect the structural model estimates (Hair et al., 2022). In recent years, VIF has been widely adopted by researchers to detect potential collinearity problems (Atoyebi & Obilade, 2024; Jony & Serradell-López, 2021; Srisa-An, 2021; Suhayat et al., 2023). Therefore, this study employs the VIF to evaluate the structural model for potential multicollinearity issues.

3.10.1.2 Evaluation of the Significance and Relevance of Structural Model Relationships and Test of Direct Relationships

The path coefficients represent the relationships in the structural model, reflecting the hypothesized associations among the constructs (Hair et al., 2022). Hair et al. (2022) recommend using bootstrapping to assess the significance of these path coefficients. As a non-parametric technique, bootstrapping involves repeatedly drawing random subsamples with replacement from the available sample data and using these resampled datasets to re-estimate the path model (Becker et al., 2023; Hair et al., 2021; Hair et al., 2022). Researchers applying PLS-SEM must rely on bootstrapping for statistical inference (Becker et al., 2023; Hair et al., 2021; Hair et al., 2022).

More specifically, when researchers are required to examine the significance of all structural model relationships, Hair et al. (2022) recommend reporting bootstrap

confidence intervals because confidence interval (CI) can provide additional information about the stability of model estimates. Likewise, many studies have examined the significance of path coefficients using bootstrap confidence intervals (Faraz et al., 2021; Kumari, 2020; Ma et al., 2021). Therefore, this study employs bootstrap confidence intervals to assess the significance of path coefficients. A significant effect is inferred when the confidence interval for an estimated coefficient does not include zero (Hair et al., 2022). In the present study, this statistical test is used to examine the hypotheses regarding the direct relationships, specifically H1 through H6.

Specifically regarding bootstrap confidence intervals, according to Cheah et al. (2023c), researchers should report the bootstrap confidence interval method, significance level, number of bootstrap subsamples, random number generator, and test type when assessing the structural model. With regard to the bootstrap confidence interval method and significance level, Aguirre-Urreta and Rönkkö (2018) found that the percentile method exhibits optimal performance. They point out that, using bootstrap estimations, the percentile method determines the 2.5% and 97.5% percentiles (at a 5% significance level) of a parameter value's distribution, which serve as the lower and upper bounds of the confidence intervals. Meanwhile, Hair et al. (2022), Becker et al. (2023), and Cheah et al. (2023c) also recommend that researchers employ this method. Consequently, this study adopts the percentile method and a 5% significance level.

Regarding the number of bootstrap subsamples, Hair et al. (2022) and Becker et al. (2023) state that researchers should use a minimum of 10,000 subsamples. Furthermore, Hair et al. (2022) note that using a larger number of bootstrap subsamples yields substantially consistent results, providing a solid basis for drawing conclusions from model estimates. Therefore, this study employs 20,000 bootstrap subsamples. With respect to the random number generator, Cheah et al. (2023c) point out that instead of using a random seed, a fixed seed can be applied to ensure replicability and eliminate concerns about result variability. As a result, the present study adopts the fixed seed option as the random number generator.

Regarding the test type, the one-tailed test is recommended when the hypothesis postulates that the coefficient has a specific direction (positive or negative), whereas the two-tailed test is recommended when no directional assumption is made about the coefficient in the context of PLS-SEM (Cho & Abe, 2013; Cheah et al., 2023a; Kock, 2015). Since no assumptions are made regarding the sign (i.e., positive or negative) of the coefficients in any of the present study's hypotheses, a two-tailed test is adopted.

After testing the significance of structural model relationships, assessing the relevance of significant relationships should be prioritized (Hair et al., 2022). A larger path coefficient indicates a stronger effect on the endogenous latent variable

and greater predictive power (Hair et al., 2022; Manley et al., 2020). Therefore, researchers should compare the relative magnitudes of path coefficients: the exogenous variable with the highest path coefficient has the greatest influence on the endogenous variable and should be considered a key construct in explaining it. In contrast, even if statistically significant, an exogenous variable with a very small path coefficient may not warrant substantial attention (Hair et al., 2022).

3.10.1.3 Assessment of the Model's Explanatory Capabilities

Building on the statement from Hair et al. (2022), the coefficient of determination (R^2) value is the most widely used metric to assess the explanatory power of the structural model. R^2 that ranges from 0 to 1 denotes the sum of the combined effects of the exogenous latent variables on the endogenous latent variable, the larger levels of explanatory power are indicated by larger R^2 values (Hair et al., 2022). In accordance with the guideline, R^2 values of 0.75, 0.50, and 0.25 are regarded as substantial, moderate, and weak (Hair et al., 2019a). Additionally, R^2 value is utilized to assess the explanatory power of the model by many investigators (Liengaard et al., 2020; Panggati et al., 2022; Sumanri et al., 2024). As a consequence, R^2 value is embraced to measure the explanatory power of the structural model in the current study.

Besides that, relying on f^2 effect size, the investigators can further employ R^2 values to assess the strength of structural model associations, the f^2 value can reveal the

degree to which an exogenous construct can contribute to the comprehension of an endogenous construct (Becker et al., 2023; Cohen, 2013; Hair et al., 2022). As a result, in addition to R^2 value, f^2 effect size will be paid attention to by the current investigation.

3.10.1.4 Evaluation of the Model's Predictive Capabilities

In order to make sure that a PLS path model is helpful and generalizable from the perspective of decision-making, the researchers ought to evaluate their model's out-of-sample predictive power, which is called the predictive power (Hair et al., 2022). An essential component of every research project is to evaluate the predictive power of a statistical model (Shmueli et al., 2019). The $PLS_{predict}$ procedure developed by Shmueli et al. is the main approach used to evaluate a PLS path model's prediction power (Hair et al., 2022; Shmueli et al., 2016; Shmueli et al., 2019).

At the same time, some investigators completed the assessment of PLS path model's predictive capabilities utilizing the $PLS_{predict}$ procedure (Cheah et al., 2023b; Subhaktiyasa, 2024; Taufiq-Hail et al., 2023). The $PLS_{predict}$ procedure is characterized as an advanced evaluation technique committed to prediction (Cheah et al., 2023b; Taufiq-Hail et al., 2023). Besides that, the evaluation of out-of-sample prediction preciseness is improved by virtue of SmartPLS 4 (Cheah et al., 2023c).

First and foremost, during the execution process of the $PLS_{predict}$, the researchers make the operation by making a series of decisions, including selecting the number of folds, the number of repetitions, and the prediction statistics which requires the researchers to take advantage of the mean absolute error (MAE) and the root mean square error (RMSE) to evaluate the predictive power of their model (Hair et al., 2022; Shmueli et al., 2019).

After operating the $PLS_{predict}$, the researchers are required to pay attention to the explanation of consequence. To be specific, the researchers ought to investigate $Q^2_{predict}$ value of each indicator from the PLS-SEM analysis, a negative $Q^2_{predict}$ value offers the implication of the lack of the predictive power of the model (Shmueli et al., 2019; Hair et al., 2022). For those indicators with $Q^2_{predict}$ being more than 0, after conducting the comparison of each indicator' RMSE (or the MAE) value produced by the PLS-SEM analysis with those produced by the naïve linear regression model (LM) benchmark model, the researchers can obtain the results of assessment of the model's predictive capabilities (Hair et al., 2022; Shmueli et al., 2019).

The present study abides by the recommendations from Hair et al. (2022) of setting the number of folds is 10 and using 10 repetitions. After obtaining the $PLS_{predict}$ result report, this study investigates the $Q^2_{predict}$ value initially. Once the $Q^2_{predict}$ values of all the indicators are more than zero, it means that the comparison will be undertaken in the following steps. In the execution process of the comparison of each indicator'

RMSE (or the MAE) value, Hair et al. (2022) advise routine use of the RMSE, which is typically the favored default prediction statistic. As a conclusion, the present study attempts to compare the RMSE values yielded by the PLS-SEM analysis with those yielded by the naïve LM benchmark model.

This study follows the established rules of thumb for assessing predictive power in PLS-SEM: when the RMSE (or MAE) values for all indicators are lower than those of the naïve LM benchmark, the model is considered to have high predictive power. If a majority (or an equal number) of indicators exhibit lower error values, this suggests medium predictive power. If only a minority of indicators outperform the benchmark, the model is deemed to have low predictive power. If none of the indicators show lower error values, the model is concluded to lack predictive power.

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3.10.2 Test of Mediating Relationships

Mediation occurs when a mediator construct intervenes in the relationship between two directly related constructs; more specifically, a change in the mediator resulting from the exogenous construct leads to a change in the endogenous construct (Hair et al., 2022; Latan et al., 2023; Hayes, 2022). Researchers can confirm the underlying mechanisms of the cause-and-effect relationship between an exogenous and an endogenous construct by examining the strength of the mediator's associations with these constructs (Hair et al., 2022; Latan et al., 2023). Scholars recommend that

researchers use bootstrap confidence intervals to test mediating effects (Hair et al., 2022; Streukens & Leroi-Werelds, 2016).

Moreover, many researchers have used bootstrap confidence intervals to examine mediating relationships in PLS-SEM analyses (Fawaid et al., 2022; Gašić & Berber, 2023; Sarstedt et al., 2020). Consequently, bootstrap confidence intervals are employed in this study to test the mediating relationships. The criterion for assessing a mediating relationship is whether zero lies within the lower and upper bounds (Hayes, 2009; Hair et al., 2022). If the 95% confidence interval excludes zero, researchers can conclude that the mediating effect exists (Hayes, 2009; Hair et al., 2022). In this study, this statistical test is applied to examine the hypotheses concerning the mediating relationships, including H7, H8, and H9.

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3.10.3 Test of Moderating Relationships

A moderating relationship exists when the association between two constructs is not constant but depends on the values of a third variable, known as a moderator variable (Hair et al., 2022; Latan et al., 2023; Hayes, 2022). According to Cheah et al. (2023c), the two-stage approach is widely used to evaluate moderating effects in SmartPLS 4.1, as it streamlines the modeling procedure, enhances statistical power and interpretability, and improves model evaluation. Therefore, this study adopts the two-stage approach to examine the moderating relationship.

According to Hair et al. (2022), the moderating model must meet the requirements for both measurement and structural model assessment. With respect to measurement model evaluation, it is unnecessary in this study because the moderator variable has only a single indicator. Regarding structural model evaluation, particular attention should be paid to the f^2 effect size of the interaction term (Becker et al., 2023; Hair et al., 2022).

Concretely, the f^2 effect size of the interaction term measures the degree to which the moderator contributes to explaining the endogenous construct (Hair et al., 2022) and can be used to assess whether the moderating effect is substantial (Becker et al., 2023). Furthermore, in analyzing the interaction term's effect, f^2 values of 0.005, 0.01, and 0.025 are conventionally classified as small, medium, and large effect sizes, respectively (Becker et al., 2023; Hair et al., 2022; Hair et al., 2021).

More importantly, when assessing whether a moderating relationship exists, researchers should primarily focus on the significance of the interaction term (Hair et al., 2022). Likewise, numerous studies have employed the interaction term to examine the moderating effect (Ahli et al., 2024; Iranmanesh et al., 2023; Jamali et al., 2022). According to Hair et al. (2022), the significance of the interaction term is evaluated using bootstrapping; if the 95% bootstrap confidence interval for the effect of the interaction term does not include zero, researchers can conclude that the

interaction effect is significant, thereby supporting the presence of a moderating effect.

Furthermore, the moderating effect should be assessed through simple slope analysis when a continuous moderator is examined (Latan et al., 2023). Simple slope analysis helps researchers enhance their understanding of moderation results and draw valid conclusions (Hair et al., 2022). In addition, based on findings from simulation studies, scholars recommend conducting tests of moderating effects using standardized data (Becker et al., 2018). Therefore, the present study employs bootstrapping and standardized data to test the moderating relationships. This statistical approach is applied to test the hypotheses concerning the moderating relationships, including H10 and H11.

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3.11 Pilot Study

Prior to collecting actual data, the pilot study serves as an initial test to evaluate the reliability of the measurement instruments (Zikmund et al., 2013). As the first step in the overall research process, the pilot study is a smaller-scale investigation that aids in designing and refining the main study, with the purpose of enhancing its quality and efficiency (In, 2017).

Although the pilot study primarily falls within the domain of survey research (Clark et al., 2022), the big data analytics approach can adopt it due to their shared

characteristics in quantitative research. Through the pilot study, researchers employing the big data analytics approach can assess whether data collection proceeds smoothly and whether it is necessary to omit a particular item, ensuring that all data can be collected within the scheduled timeframe.

According to Hazzi and Maldaon (2015), reliability is a crucial consideration that the researchers should make for the pilot study, and the most widely used measure for the assessment of reliability is Cronbach's alpha, thus, Cronbach's alpha is suggested to contribute to the assessment of reliability in pilot study. According to Hair (2022), the internal consistency reliability ought to be 0.6 or higher. Therefore, the present study undertakes the pilot study with Cronbach's alpha, which ought to be 0.6 or higher.

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In addition, scholars suggest that the sample size for a pilot study should constitute 10% of the projected sample for the main study (Connelly, 2008). Therefore, this study employs a simple random sampling method to select a sample of 30 for the pilot phase. To conduct the pilot study, 30 Chinese web dramas were sampled, yielding 360 pieces of structured data and 1,201,293 pieces of unstructured data using GooSeeker and Miniconda software. After performing reliability evaluation via SmartPLS 4.1, the study obtained Cronbach's alpha coefficients for the relevant constructs, as presented in Table 3.5 below.

Table 3.5

Reliability Test Results in Pilot Study

Constructs	Number of Attributes	Cronbach's alpha
AS	5	0.914
VM	4	0.893
WDE	6	0.863
SME	5	0.904

Note: AS: web drama audience satisfaction;
VM: Web drama viewing motivation;
WDE: Web drama exposure;
SME: Web drama audience's social media engagement;
The same below.

The results presented in Table 3.5 above show the Cronbach's alpha coefficients for the independent variable, dependent variable, and mediating variables, ranging from 0.863 to 0.914, indicating that the reliability of this pilot study is acceptable. As a consequence, it can be concluded that each construct in the current study is free of unnecessary attributes. Subsequently, big data acquisition and analysis will be conducted for the present study, which comprises 21 attributes derived from five latent variables.

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3.12 Ethics

The communication researchers have a responsibility to comply with the ethics (Keyton, 2022). Although the unobtrusive measures offer a avoidance of the ethical issues which are covered by other data-collection methods, there are still some possible hazards to be aware of (Babbie, 2020). As a consequence, like any other

type of study, it is crucial to take the ethical implications into account before utilizing big data in research.

The challenges concerning ethics of big data analytics approach are required to be discussed seriously. Babbie (2020) points out that the risks of ethical issues may be from the absence of principle of confidentiality and illegal acquisition of data. Scharrer and Ramasubramanian (2021) concentrate on the ethics of big data analytics approach from the perspective of critical data studies, such as privacy and surveillance. Clark et al. (2022) note that, concerns over data protection, consent, and confidentiality are growing in significance as big data usage increases.

Specifically, Keyton (2022) emphasizes that the communication researchers are supposed to prevent bodily or psychological harm to participants happening, meanwhile, they ought to protect the privacy and anonymity of participants, in addition, the ethical issues of online technology application need to be identified in communication research, furthermore, the communication researchers are required to make sure that the data and consequences obtained are accurate. Besides that, in accordance with Hosseini et al. (2022), the researcher who are committed to big data analytics approach ought to abide by the guidelines of truthfulness, diligence, transparency, efficiency, deference to subjects, and social duty. Based on these literature above, it is necessary to take into account the ethics of this study, especially the ethics of big data analytics approach.

First and foremost, the big data analytics approach adopted by this study can ensure that the present study does not interfere with the participants, accordingly, there is no bodily or psychological harm to participants. Moreover, in the present study, the big data technology employed in this research is provided by GooSeeker software, which is legal and widely utilized in China (Qiu & Zhang, 2021; Xie et al., 2024; Zhang et al., 2020). In the process of big data crawling, all the data of the present study are from public Internet information, this study will not and does not have the ability to collect any privacy information of the research subjects, such as the real name, gender, age, date of birth, and home address, therefore, there are no violations of individuals' privacy and anonymity.

Besides that, the present study ensures that the data and consequences gained are accurate, there is no plagiarism or fabrication. Additionally, the guidelines of truthfulness, diligence, transparency, efficiency, deference to subjects, and social duty are followed by this study strictly. Furthermore, all the major Internet companies associated with this study, such as Baidu Inc. (2024), Tencent Inc. (2024), Alibaba Group (2024), promise to comply with the relevant laws and regulations, like *Personal Information Protection Law of the People's Republic of China,* in order to protect users' private information and data security. Meanwhile, they are committed to data security and privacy protection by many measures and approaches such as the establishment of data management committee, formation of security

research team, and establishment of data privacy and security management system (Alibaba Group, 2024; Baidu Inc., 2024; Tencent Inc., 2024).

In the meantime, the pumping from Internet troll army may cause harm to society (Howard, 2020; Schirch, 2021). In China, it is regarded as the illegal behavior (Ji et al., 2024; Yang & Wang, 2024). In the face of the pumping from the humanity and robot on the Internet, the Chinese public security department has launched a series of severe crackdowns (Xiao, 2024; Yin, 2023). Meanwhile, many major Internet companies have implemented measures to combat manipulation by coordinated online troll networks (Baidu Inc., 2024; Tencent Inc., 2024), for instance, Baidu Inc. has established the Baidu reporting platform (the link is http://jubao.baidu.com/jubao/) in order to further prevent and combat Internet troll army. The fight against the pumping from Internet troll army will prevent the fake audience and untruth comments, bringing to a relatively pure Internet environment.

Last but not least, many scholars have embraced big data analytics approach while complying with ethical requirements. McQuail and Deuze (2020) advocate for the media sector to seek big data on audience. The combination of big data analytics approach and media effect evaluation performed by Zhou and Zhao (2021) brings more encouragement and inspiration to communication researchers. Babbie (2020), Clark et al. (2022), and Boyle and Schmierbach (2024) encourage social science researchers to embrace the social media big data analytics approach due to its

significant potential and promising future in social research. In a word, on the premise of complying with ethical requirements, investigators ought to be devoted to communication studies with big data analytics approach.

3.13 Chapter Summary

The research methodology is crucial, as it determines the validity of the research findings and conclusions. This chapter is divided into thirteen sections. The first section provides an introduction to the chapter. Next, the second section presents the research philosophy of this study. Subsequently, the third section provides the research design of the study, including research approach, time dimension, unit of analysis, population and sampling, sampling frame, sample size, and sampling technique.

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Additionally, the fourth section outlines the operationalization of each construct. Next, the fifth section presents the data collection procedures, including data collection techniques and specific implementation steps. Following this, the sixth section describes the statistical analysis procedures, which consist of data preparation, assessment of underlying statistical assumptions, and descriptive analysis.

Subsequently, the seventh section introduces PLS-SEM. The eighth, ninth and tenth sections then detail the PLS-SEM application procedure, covering CCA, evaluation of the measurement and structural models, and testing of mediating and moderating

relationships. After the pilot study described in the eleventh section, ethical considerations are discussed in the twelfth section. The chapter concludes with a summary in the thirteenth section.

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CHAPTER FOUR

DATA ANALYSIS AND RESULTS

4.1 Introduction

The present study aims to develop a comprehensive predictive model for audience satisfaction in Chinese web dramas through a big data analytics approach, informed by UGT and CCT. Based on the relevant literature, the preceding chapters propose eleven hypotheses concerning the relationships among five variables: web drama audience satisfaction, web drama viewing motivation, web drama exposure, audience social media engagement, and social media community size. These hypotheses establish both a conceptual model and a hypothesized predictive model. Following big data collection and sentiment analysis, this chapter provides a comprehensive and in-depth examination of these constructs, presenting the key findings of the study.

This chapter consists of nine sections. First, the introduction of the chapter is presented in the first section. Next, the second section describes the preparation of data analysis using SPSS 29.0, including monotonicity assessment, logarithmic transformation, handling of missing data and outliers, and data normalization. Subsequently, the third section presents the preliminary analysis conducted with SPSS 29.0, which includes assessments of the absence of severe non-normality, linearity, homoscedasticity, and independence of errors.

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Subsequently, the fourth section presents the descriptive analysis, which includes brief descriptive statistics of unstructured data, descriptive statistics of the 288 Chinese web dramas, and descriptive statistics of the variables. In addition, the fifth section reports the execution of CCA and the assessment of the measurement model using SmartPLS 4.1. Following this, the sixth section presents the hypothesis testing, including the examination of direct, mediating, and moderating relationships with SmartPLS 4.1. Furthermore, the seventh section discusses the extent to which the research questions and objectives have been achieved. The application of the predictive model developed in this study is presented in the eighth section. Finally, the ninth section provides a summary of this chapter.

4.2 Preparation for Data Analysis

The primary objective of this section is to prepare sample data for subsequent analysis. Following the big data analytics framework (Babbie, 2020), this study conducted an efficient and systematic collection of large-scale data from August 18, 2024, to October 3, 2024. A total of 16,057,255 pieces of unstructured data were gathered from leading Chinese social media platforms, including Weibo, Douban, Zhihu, and Xiaohongshu. Additionally, 3,744 structured data records were obtained directly from prominent Chinese digital sources such as Baidu, 360 Search, Maoyan, Douban, TikTok (China), Kwai (China), WeChat, and Weibo. These structured data points, containing predefined attribute values, are suitable for direct use in statistical analysis.

From October 3, 2024, to October 16, 2024, this study used GooSeeker and Miniconda software to perform sentiment analysis on 16,057,255 pieces of unstructured data, resulting in the extraction of 2,304 structured data records to serve as values for relevant attributes. In total, this study compiled 6,048 structured data records, which are suitable for direct use in subsequent statistical analysis.

After successfully completing the acquisition of all attribute values, which comprised a total of 6,048 structured data records, this study entered the data into an Excel spreadsheet. The dataset was then imported into SPSS 29.0 for further analysis. Following this, data cleaning and polishing were conducted to prepare for subsequent data analysis. To be specific, it involves monotonicity assessment, logarithmic transformation, handling of missing data and outliers, and data normalization, which address five key challenges in data analysis preparation (Baydoğmuş, 2021; Baddoo et al., 2021; Elkhouly et al., 2023; Hair et al., 2019b; Henderi et al., 2021; Kline, 2023; Mirzaei et al., 2022; Noel, 2021; Roni & Djajadikerta, 2021). The following section provides a detailed explanation of the procedures and outcomes.

To begin with, this study conducted an investigation of monotonicity. After visually inspecting the 6,048 structured data records, which represent the values of 21 attributes for 288 samples, no instances of monotonic patterns were observed. This indicates that the big data exhibit strong diversity and high credibility. Following this,

logarithmic transformation was performed using SPSS 29.0 to eliminate potential undesirable characteristics of the variables. As previously stated, big data span multiple orders of magnitude, which may lead to severe distributional non-normality and compromise model robustness. For instance, among the original data for VM1, 24 web dramas exhibit single-digit values (1 – 9), 68 display two-digit values (10 – 99), 76 fall within the three-digit range (100 – 999), and 120 reach four-digit levels (1000 – 9999), indicating a wide distribution spanning multiple orders of magnitude, thus necessitating logarithmic transformation.

The subsequent concern is the issue of missing data. As previously mentioned, the target population of this study includes all Chinese web dramas with accessible big data from Tencent Video, iQIYI, Youku, Mango TV, Bilibili, and SOHU Video. Meanwhile, the sample in this study comprises the sampled Chinese web dramas sourced from Tencent Video, iQIYI, Youku, Mango TV, Bilibili, and SOHU Video. Those web dramas lacking sufficient data are excluded from the research sample, making the likelihood of encountering missing data exceedingly low. Following the completion of big data collection and sentiment analysis, this study obtained a total of 6,048 structured data records representing the values of 21 attributes. No instances of missing data were observed.

Next, an investigation was conducted into potential outliers. Big data possess the characteristics of high volume and variety (Babbie, 2020; Clark et al., 2022;

Castellani & Rajaram, 2021; De Mauro et al., 2015; Hair et al., 2019b), and as a consequence, data acquired through the big data analytics approach do not have an upper limit value in empirical studies. In other words, the big data analytics approach may face greater challenges from outliers. Therefore, this study places significant emphasis on the detection and handling of outliers. Appropriate treatment of outliers in the dataset is necessary to ensure the accuracy of research findings in big data analysis (Ridzuan & Zainon, 2022).

In practice, this study employed the boxplot as a method for detecting outliers (Kline, 2023; Roni & Djajadikerta, 2021; Tukey, 1977). A boxplot provides a graphical summary of the data distribution across its entire range. The boundaries of the box are defined by the hinges, which approximately correspond to the first quartile (25th percentile) and the third quartile (75th percentile), while a line within the box represents the median, or second quartile (50th percentile) (Kline, 2023). Lines extending from the box, known as whiskers, connect to the minimum and maximum values that fall within 1.5 times the interquartile range (IQR) beyond the hinges. Data points lying beyond these whiskers are identified as outliers (Kline, 2023).

Table 4.1 presents the outlier detection results for all attributes. After identifying the outliers, this study mitigated their influence by recoding them to values consistent with the nearest non-extreme observations (Kline, 2023; Kwak & Kim, 2017; Roni & Djajadikerta, 2021). Subsequently, Z-score normalization was applied to standardize

the sample data using SPSS 29.0 for further analysis. Following normalization, a preliminary analysis of the sample data was conducted.

Table 4.1

Detection Results of Outliers

Construct	Attribute	Lower and Upper Bounds for Detection of Outlier	Outliers' Volume
AS	AS1	[-0.352, 3.258]	9
	AS2	[-0.961, 2.529]	3
	AS3	[-0.444, 1.600]	8
	AS4	[-0.058, 2.253]	4
	AS5	[1.246, 2.319]	7
VM	VM1	[3.755, 11.875]	1
	VM2	[2.232, 10.495]	2
	VM3	[3.443, 6.939]	14
	VM4	[3.825, 7.292]	5
WDE	WDE1	[2.392, 9.692]	2
	WDE2	[-0.827, 10.358]	1
	WDE3	[8.486, 9.527]	14
	WDE4	[-1.453, 7.316]	8
	WDE5	[7.431, 14.724]	18
	WDE6	[4.162, 14.877]	13
SME	SME1	[-4.171, 17.043]	2
	SME2	[-2.055, 10.017]	2
	SME3	[-1.441, 10.203]	4
	SME4	\	0
	SME5	[0.165, 8.795]	1
SMCS	SMCS1	[-2.339, 5.192]	6

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4.3 Preliminary Analysis

This part offers a preliminary analysis of the data acquired, that is, an argument of the underlying statistical assumptions of the current investigation. The preliminary analysis consist of the absence of severe non-normality, linearity, homoscedasticity

and independence of error (Hair et al., 2019b; Hair et al., 2022). The current study utilized 288 viable observations to conduct the preliminary analysis.

4.3.1 Absence of Severe Non-normality

As has been noted by Hair et al., (2022), it is essential to ensure that the sample data do not deviate extremely from normality. Therefore, the absence of severe non-normality ought to be examined carefully in this study. To be specific, kurtosis and skewness tests are employed with SPSS 29.0 for verifying the absence of severe non-normality (Hair et al., 2022). In accordance with Hair et al. (2019b), the researcher can embrace the rule of thumb based on the skewness and kurtosis values to evaluate the normality, that the values of them are between ±2.58 (0.01 significance level) and ±1.96 (0.05 significance level) are the most frequently acceptable.

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To go a step further, Hair et al., (2022) make the clarification that a skewness value or kurtosis value between ±1 is considered as great, whereas, a value between ±2 is usually regarded as acceptable, considered to be an indication of significant non-normality are values both beyond -2 and +2. Besides that, the sample size is also a vital consideration concerning normality (Kim, 2013; Orcan, 2020). Concretely, with regard to medium-sized samples ($50 < n < 300$), if the absolute values of skewness or kurtosis exceed 3.29 (an alpha level of 0.05), it can be inferred that the sample distribution is non-normal (Kim, 2013; Orcan, 2020). On top of that, Kline

(2023) points out that the rule of thumb for serious non-normality is that the absolute univariate skewness and kurtosis values are more than 2.0 and 7.0 respectively.

Building on the statements from Hair et al. (2022), it is of importance to verify that the sample data do not depart from normality severely. Accordingly, the present study embraces the guideline for severe non-normality from Kline (2023) that the absolute value of skewness is greater than 2.0 and the absolute value of kurtosis is greater than 7.0. Adopting 288 valid samples, the current study assessed the skewness and kurtosis of the present data and displayed the outcomes in Table 4.2 below.

Table 4.2 below manifests the skewness and kurtosis values of all constructs. The outcomes in Table 4.2 reveal that each skewness or kurtosis value of this study falls within the range of ±1, they are characterized as a great normal distribution by Hair et al. (2022). Meanwhile, they also mean the absence of severe non-normality in the current investigation (Kline, 2023).

Table 4.2

Skewness and Kurtosis Values of All Constructs

Construct	N	Skewness	Std. Error	Kurtosis	Std. Error
AS	288	-0.030	0.144	-0.794	0.286
VM	288	-0.289	0.144	-0.706	0.286
WDE	288	-0.236	0.144	-0.344	0.286
SME	288	0.195	0.144	-0.857	0.286
SMCS	288	-0.194	0.144	0.145	0.286

4.3.2 Linearity Assumption

This research executed the linearity assumption test by the utilization of scatter-plots (Hair et al., 2019b; Roni & Djajadikerta, 2021; Tabachnick, 2019). To be specific, the assessment of linearity assumption can be performed by a scatter-plot of the standardized predicted values against the standardized residuals (Casson & Farmer, 2014; Hair et al., 2019b). Supposing that the residuals are randomly dispersed around the horizontal line, exhibiting no apparent pattern, and the standardized residual does not change with the variation of standardized predicted values, the researcher can determine that the linearity assumption is valid for the sample data (Casson & Farmer, 2014). The current study shows the consequence in Figure 4.1 below.

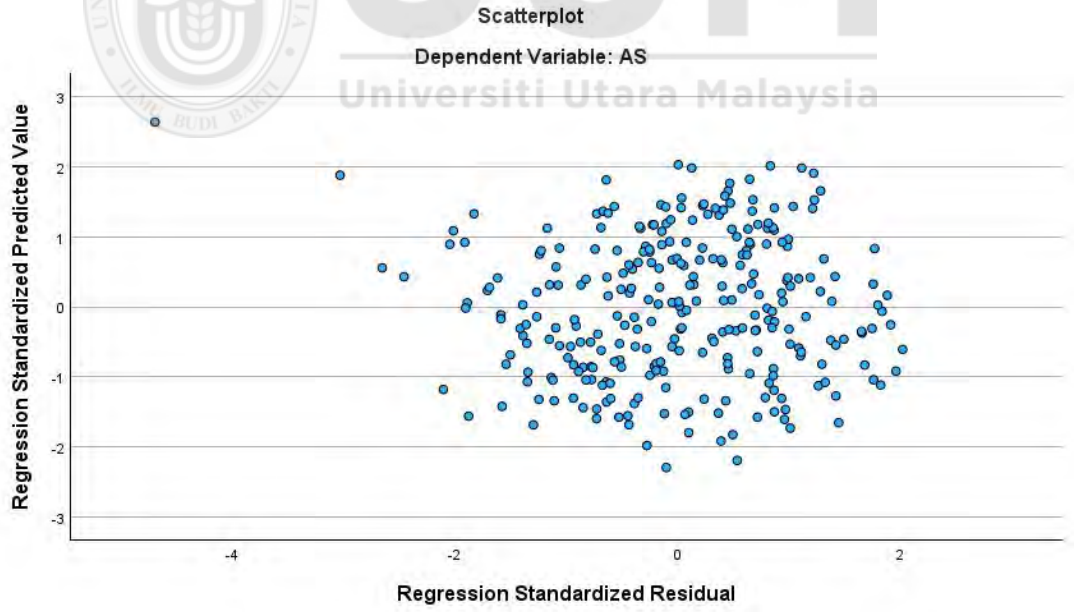


Figure 4.1 Scatter-plot of the Standardized Predicted Values against the Standardized Residuals

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From Figure 4.1 above, the data points exhibited in this scatter-plot are randomly distributed around the horizontal line, displaying no discernible pattern, the standardized residual does not vary with the fluctuations in the standardized predicted values, as a consequence, the present study supports the linearity assumption of sample data.

4.3.3 Homoscedasticity Assumption

The present study embraced the scatter-plot to complete this examination under the aid of SPSS (Hair et al., 2019b; Roni & Djajadikerta, 2021; Tabachnick, 2019). In detail, if the scatter-plot of the standardized predicted values against the studentized residuals presents the random equal dispersion across all data points, any indication of rising or falling residuals has not been manifested graphically, the alteration of studentized residuals is not with the variation of standardized predicted values, the researcher can infer that the homoscedasticity assumption is supported (Hair et al., 2019b; Osborne & Waters, 2002; Roni & Djajadikerta, 2021). The violation of equal dispersion can usually be depicted by cones (small distribution on one side, huge on the other) or diamonds (many points in the middle of the dispersion) (Hair et al., 2019b; Osborne & Waters, 2002). The result is manifested in Figure 4.2 below.

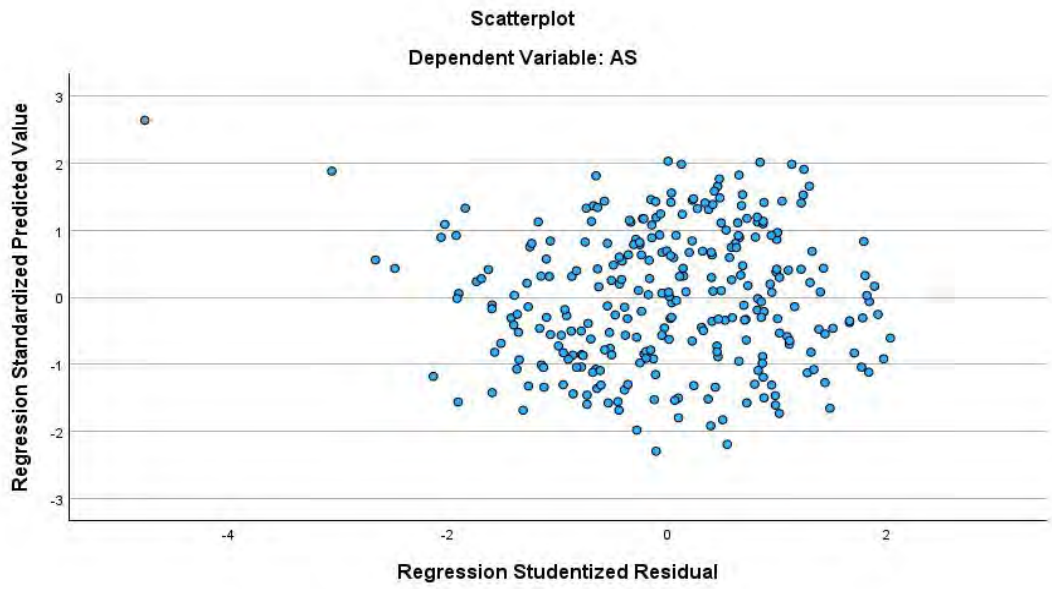


Figure 4.2 Scatter-plot of the Standardized Predicted Values against the Studentized Residuals

Figure 4.2 above displays the test outcome of the homoscedasticity assumption of this study. It presents that each point is evenly distributed above and below the line corresponding to point 0 on the vertical axis, the alteration of the studentized residuals on the horizontal axis is not with the change of the standardized predicted values on the vertical axis. Consequently, it can be uncovered that the sample data for this investigation fulfill the requirement of homoscedasticity stated by Hair et al. (2019b) and Roni and Djajadikerta (2021), the homoscedasticity assumption was supported in the present research.

4.3.4 Independence Assumption of Error

The data collection procedure and the use of time series data are two common sources of dependent errors, which can violate the assumption of uncorrelated errors (Hair et al., 2019b). With the assistance of SPSS 29.0, the Durbin-Watson statistic

was employed to assess error autocorrelation (Flatt & Jacobs, 2019; Tabachnick, 2019). The Durbin-Watson statistic ranges from 0 to 4, with a value close to 2 indicating no significant autocorrelation, which is the desired outcome (Flatt & Jacobs, 2019). Values below 1 suggest positive autocorrelation, whereas values above 3 indicate negative autocorrelation (Flatt & Jacobs, 2019). After conducting the analysis in SPSS 29.0, the results showed a Durbin-Watson value of 1.95. Given that this value is close to 2, it can be concluded that there is no evidence of autocorrelated errors in the sample data of this study.

In summary, the statistical assumptions underlying this study, including the absence of severe non-normality, linearity, homoscedasticity, and independence of errors, are supported by the test results. Therefore, descriptive analysis and model evaluation will be conducted in the subsequent analysis.

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4.4 Descriptive Analysis

Descriptive statistics illustrate the representation of sample data in both numerical and visual formats (Croucher & Cronn-Mills, 2024). In this study, the sample data include real-time statistical datasets from sampled Chinese web dramas. Notably, among these data, large-scale social media comments constitute unstructured, text-only data. Consequently, the descriptive analysis in the current study covers three aspects: the brief descriptive statistics of unstructured data, the descriptive

statistics of the sampled 288 Chinese web dramas, and the descriptive statistics of the variables. These aspects are discussed in the following sections.

4.4.1 Brief Descriptive Statistics of Unstructured Data

Relying on GooSeeker software, this study accomplished an efficient collection of 16,057,255 pieces of unstructured data from prominent Chinese social media platforms, including Weibo, Douban, Zhihu, and Xiaohongshu. Among these unstructured data, a total of 12,261,134 pieces (approximately 76.3%) come from Weibo, whereas the amounts from Douban, Xiaohongshu, and Zhihu are significantly lower.

Concretely, Douban contributes 1,844,407 pieces of unstructured data (approximately 11.5%), followed by Xiaohongshu with 1,011,273 pieces (approximately 6.3%). Zhihu provides the smallest amount, totaling 940,441 pieces (approximately 5.9%). The specific distribution is presented in Figure 4.3 below, which indicates that the audience for Chinese web dramas is most active on Weibo, followed by Douban among the four prominent social media platforms in China.

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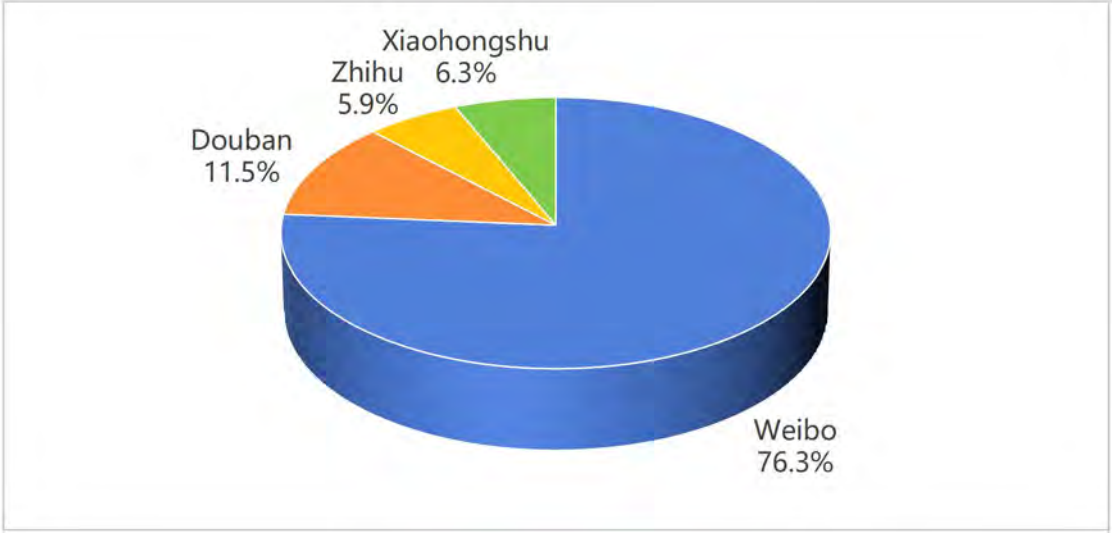


Figure 4.3 Distribution of Unstructured Data on Social Media

4.4.2 Descriptive Statistics of 288 Chinese Web Dramas

This study relies on data from the Maoyan app to conduct descriptive statistics on 288 Chinese web dramas, examining their release time, genre, and broadcasting platform, as presented in Table 4.3 below. With regard to release time, the highest number of samples was released in 2020 (60 samples, 20.74%), followed by 2021 (55 samples, 19.12%). The data for 2024 are only available up to August 15th, 2024, resulting in the smallest sample size for that year (13 samples, 4.4%). The research employs a combination of stratified and systematic sampling, ensuring that years with a larger volume of web dramas in the dataset yield proportionally more samples.

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Table 4.3

Descriptive Statistics of 288 Chinese Web Dramas

Release Time	Frequency	Percentage (%)
2018	40	13.79%
2019	42	14.72%
2020	60	20.74%
2021	55	19.12%
2022	39	13.56%
2023	39	13.67%
2024 (As of August 15th)	13	4.4%
Genre		
Comedy Drama	37	12.85%
Martial Arts Drama	12	4.17%
Action Drama	10	3.47%
Fantasy Drama	4	1.39%
Historical Biographical Drama	3	1.04%
War Military Drama	4	1.39%
Urban Drama	53	18.40%
Criminal Investigation Drama	10	3.47%
Youth Idol Drama	48	16.67%
Romantic Drama	155	53.82%
Science Fiction Drama	6	2.08%
Suspense Drama	59	20.49%
Thriller Drama	1	0.35%
Costume Drama	81	28.13%
Broadcasting Platform		
Tencent Video	126	43.75%
iQIYI	131	45.49%
Youku	66	22.92%
Mango TV	46	15.97%
Bilibili	4	1.39%
SOHU Video	9	3.13%

N = 288.

Note: A given web drama may belong to multiple genres and be distributed across multiple platforms, resulting in the total counts for overall genres and Chinese web dramas on the six platforms exceeding the sample size of 288.

Source: Maoyan app.

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Among the web drama samples analyzed, romantic dramas constitute the largest genre category, accounting for 155 samples (53.82% of the total), followed by costume dramas as the second most prevalent genre with 81 samples (28.13%). In contrast, thriller dramas represent the smallest category in this study, with the fewest sampled instances.

In terms of broadcasting platforms, iQIYI hosts the largest number of Chinese web drama samples in this study, with 131 entries accounting for 45.49% of the total. Tencent Video follows with 126 samples, representing 43.75% of the overall count. Bilibili has the fewest samples, contributing only 4 web dramas, or 1.39% of the total.

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4.4.3 Descriptive Statistics of the Variables

The descriptive analysis of quantitative variables encompasses the descriptive statistics of measures of central tendency and measures of dispersion (Andrade, 2020). Specifically, measures of central tendency primarily include mean, median, and mode, while measures of dispersion essentially include range, variance, and standard deviation (Bougie & Sekaran, 2019; Boyle & Schmierbach, 2024; Croucher & Cronn-Mills, 2024).

Due to the high volume, variety, and widespread dispersion of big data (Babbie, 2020; Clark et al., 2022; Hosseini et al., 2022), the dataset is unlikely to exhibit a

mode. Consequently, this study excludes mode as a measure in its descriptive analysis. In summary, this research conducts descriptive statistics of the variables using the measures of mean, median, range, variance, and standard deviation. Meanwhile, the construct scores across the 288 sampled web dramas warrant further discussion.

First, if the difference between the mean and median is substantial, this suggests that the sample data may be not normally distributed (Zhou, 2017). Additionally, the standard deviation should be less than the mean; if it is comparable to or exceeds the mean, the data may be considered to exhibit a non-normal distribution (Livingston, 2004).

Notably, the prior sample data were obtained using Z-score normalization, which transformed the original data into values with a mean of 0 and a standard deviation of 1. For these standardized data, conducting descriptive analysis on the means and standard deviations of the variables would be redundant. To address this issue, this study re-standardized all attribute data after logarithmic transformation and outlier processing using the min-max [0, 1] normalization method.

Min-max [0, 1] normalization is the process of transforming data into a specified range between 0 and 1 by applying linear transformations to the raw data, enabling balanced comparisons of values before and after the procedure (Baydoğmuş, 2021;

Elkhouly et al., 2023; Henderi et al., 2021). Min-max [0, 1] normalization was applied solely to the data included in the descriptive statistics, while Z-score normalization was used for all other data processing procedures throughout the study.

After applying min-max [0, 1] normalization method, this study computed the construct scores for the 288 sampled web dramas using the standardized data of the corresponding attributes through SmartPLS 4.1 and SPSS 29.0. According to Hair et al. (2022), in reflective measurement models, the PLS-SEM algorithm computes construct scores by forming a linear combination of indicators, using outer loadings as weights. Therefore, to obtain the construct scores, this study followed the recommendation of Hair et al. (2022) by first using SmartPLS 4.1 to extract the outer loadings of all attributes. The standardized attribute data for each construct were then multiplied by their respective weights (i.e., outer loadings). Finally, the resulting products were summed to compute the construct scores. It is expressed by the following formula.

$$Y = W_1X_1 + W_2X_2 + \cdots + W_nX_n$$

In this formula, Y indicates the construct score, X_1 through X_n denote the standardized attribute values, and W_1 through W_n represent the corresponding weights of the attributes (i.e., outer loadings) which are derived from SmartPLS 4.1 based on the PLS-SEM algorithm. Through calculation, this study obtained the

scores for all variables and used SPSS 29.0 to compute their mean, median, range, variance, and standard deviation; the results are presented in Table 4.4 below. Notably, the method used in this study to calculate construct scores must be based on the confirmation of the measurement model. Therefore, the assessment of the measurement model will be conducted in the following section.

Table 4.4

Descriptive Statistics of Variables

Construct	Mean	Median	Range	Variance	Standard deviation
AS	2.100	2.110	3.276	0.498	0.706
VM	1.974	2.054	3.054	0.434	0.659
WDE	2.450	2.479	4.247	0.733	0.856
SME	1.969	1.931	3.410	0.604	0.777
SMCS	0.510	0.503	1.000	0.041	0.202

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As shown in Table 4.4, the construct of web drama viewing motivation has the highest mean among the five constructs, whereas the construct of audience social media engagement has the lowest. Moreover, web drama viewing motivation also exhibits the highest median, while audience social media engagement shows the lowest. In addition, the construct of social media community size has the largest range, whereas the construct of web drama audience satisfaction has the smallest. Furthermore, social media community size displays the highest variance and standard deviation, while web drama audience satisfaction has the lowest values for both measures.

Table 4.4 shows that the differences between the means and medians are very small across the five constructs (AS: 0.010; VM: 0.080; WDE: 0.029; SME: 0.038; SMCS: 0.007). Furthermore, each standard deviation is smaller than the corresponding mean value, as shown in Table 4.4. These results indicate that the sample data are normally distributed in this study.

Meanwhile, the construct scores were further analyzed across the 288 sampled web dramas. Regarding the construct of web drama audience satisfaction, the scores ranged from 0.418 to 3.694. Specifically, the web drama *Love Between Fairy and Devil* achieved the highest score, while *Adventurer Wang Weisi: The Blue Blood Man* received the lowest. Among the top ten most viewer-satisfactory web dramas, three were released in 2022, one in 2023, and one in 2024, indicating a potential decline in the number of highly acclaimed web dramas since 2023.

In the meantime, half or more of these ten web dramas belonged to the costume drama, romantic drama, and martial arts drama genres, indicating that these three genres may be particularly favored by audiences. Furthermore, eight of the ten web dramas were available on iQIYI (with three being exclusive to the platform), four on Youku, and three on Tencent Video, reflecting the dominant market positions of these three streaming platforms.

Meanwhile, among the bottom ten web dramas in viewer satisfaction rankings, four were released in 2023, followed by two each in 2018 and 2021. Although web dramas from 2023 account for only 13.67% of the total sample, they are disproportionately represented in the least satisfactory group. Considering that the sample size for 2024 is the smallest due to data collection ending on August 15, 2024, this study suggests that the number of web dramas with very low audience satisfaction may be increasing.

Additionally, seven of the bottom ten web dramas belonged to the suspense drama genre. In the overall sample of this study, suspense dramas constitute only 59 entries (20%), yet they are overrepresented in the lowest satisfaction rankings. This indicates that, compared to other genres, suspense dramas are more likely to result in audience dissatisfaction, posing greater risks and challenges for content production. Furthermore, five of the bottom ten web dramas were available on iQIYI, four on Youku, and four on Tencent Video, suggesting that China's major streaming platforms may still fall short in implementing timely interventions to improve audience satisfaction.

Regarding the construct of web drama viewing motivation, the scores ranged from 0.275 to 3.329. Specifically, the web drama *Who Is the Murderer* achieved the highest score, while *Bionic Human* received the lowest. Among the top ten web dramas with the highest scores in viewing motivation, five belonged to the costume

drama genre, five to the fantasy genre, four to the youth idol drama genre, and four to the romantic drama genre.

With regard to the construct of web drama exposure, the scores ranged from 0.193 to 4.441. Concretely, the web drama *Mysterious Lotus Casebook* achieved the highest score, whereas *grand theft in tang* received the lowest. Among the top ten web dramas with the highest exposure score, eight belonged to the costume drama genre, seven to the romantic drama genre, and four to the youth idol drama genre.

With respect to the construct of audience social media engagement, the scores ranged from 0.450 to 3.860. Specifically, the web drama *Burning Flames* attained the highest score, whereas *Everyone in the World Is No Match for You* received the lowest. Among the top ten web dramas with the highest social media engagement score, six belonged to the costume drama genre, and six to the romantic drama genre.

Regarding the construct of social media community size, it comprised only one attribute, and the score for this construct ranged from 0.000 to 1 (notably, the minimum value was so small that it rounded to 0 when expressed to the third decimal place, while the maximum value was sufficiently close to 1 to round to 1 at the same precision level). Since this variable consists of only one attribute, there are no differences in measurement units across attributes. Therefore, the original values of this variable can be reported: specifically, social media community size ranged from

84 to 1,353,000 fans, with a mean of 104,171, a median of 38,500, a range of 1,352,916, a variance of 32,385,102,131, and a standard deviation of 179,959.

Among the 288 sampled web dramas, *Eagles and Youngster* exhibited the largest social media community size, whereas *Happiness Knocks Twice* had the smallest. Among the top ten web dramas with the largest social media community size, six belonged to the romantic drama genre, and six to the costume drama genre. The minimum and maximum values of the construct scores are presented in Table 4.5 below.

Table 4.5

Minimum and Maximum Values of Construct Scores

Construct	Minimum Value	Maximum Value
AS	0.418	3.694
VM	0.275	3.329
WDE	0.193	4.441
SME	0.450	3.860
SMCS	0.000	1

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4.5 Execution of CCA and Assessment of Measurement Model

As argued earlier, Hair et al. (2019b), Hair et al. (2020), and Hair et al. (2022) highlight that CCA comprises a sequence of procedures performed within PLS-SEM to validate both reflective and formative measurement models. Meanwhile, Hair et al. (2019b) and Hair et al. (2020) emphasize the strengths of CCA, which is beneficial for researchers committed to validating measurement models composed of linear composites.

To go a step further, Hair et al. (2022) clarify the CCA procedure as follows: First, it is essential to differentiate between the reflective measurement model and the formative measurement model due to their distinct evaluation procedures. Subsequently, based on the relevant assessment criteria, the researcher conducts the evaluation of the measurement model.

In terms of the first process, the previous statement in Chapter Three has provided a discussion of the measurement model employed in this study; that is, the reflective measurement model. According to Hair et al. (2022), the evaluation of the reflective measurement model consists of four procedures: indicator reliability, internal consistency reliability, convergent validity, and discriminant validity. The sample data in the present study are assessed sequentially according to these four steps as follows.

4.5.1 Indicator Reliability

As has been noted previously, the initial procedure in evaluating the reflective measurement model is indicator reliability, which involves analyzing the outer loadings of the indicators (Hair et al., 2022). The outer loading is supposed to be standardized at 0.708 or above, as per a widely accepted guideline (Hair et al., 2022). This study accomplished the examination of the outer loadings of all indicators by virtue of SmartPLS 4.1, obtaining the outcomes manifested in Table 4.6 below.

Table 4.6

Test Results of Indicator Reliability for the Measurement Model

Constructs	Attributes	Factor Loading
AS	AS1	0.889
	AS2	0.832
	AS3	0.865
	AS4	0.834
	AS5	0.809
VM	VM1	0.900
	VM2	0.859
	VM3	0.875
	VM4	0.888
WDE	WDE1	0.723
	WDE2	0.865
	WDE3	0.803
	WDE4	0.776
	WDE5	0.788
	WDE6	0.870
SME	SME1	0.862
	SME2	0.828
	SME3	0.883
	SME4	0.864
	SME5	0.865
SMCS	SMCS1	1.000

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As has been presented in Table 4.6 above, the factor loading values of all attributes are between 0.723 and 1, exceeding the necessary level of 0.708. It signified that the every construct accounts for over 50 percent of the variance of its indicator, the corresponding indicators shared a significant amount of commonality and are thus seized by the construct in the present research. Hence, the results in Table 4.6 above demonstrates a satisfied level of indicator reliability.

4.5.2 Internal Consistency Reliability

As stated earlier, Cronbach's alpha criterion is utilized to assess internal consistency reliability in the current research (Hair et al., 2019a; Hair et al., 2022). Cronbach's alpha is between 0 and 1 with larger values indicating greater reliability levels, it can be acceptable that the value of Cronbach's alpha exceeds 0.6 (Hair et al., 2022). Employing SmartPLS 4.1, this study achieved the Cronbach's alpha values of all constructs, which is presented in Table 4.7 below.

Table 4.7

Test Results of Internal Consistency Reliability and Convergent Validity for the Measurement Model

Constructs	Cronbach's alpha	AVE
AS	0.901	0.716
VM	0.904	0.776
WDE	0.891	0.649
SME	0.912	0.741

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Table 4.7 above displays the Cronbach's alpha values of the corresponding constructs, which range from 0.891 to 0.912. It can be discovered that they suit the request proposed by Hair et al. (2022) that the acceptable value of Cronbach's alpha is greater than 0.6. The results manifested in Table 4. above indicated that the sample data of this study possessed the satisfying internal consistency reliability. There is no existence of redundant attributes in each construct of the current study.

4.5.3 Convergent Validity

As mentioned before, AVE is utilized to evaluate the convergent validity in the current research. Relying on the explanation from Hair et al. (2022), convergent validity is commonly quantified using AVE, and the amount of AVE for each reflectively measured construct ought to be evaluated. To go a step further, according to the rule of thumb, the AVE value is supposed to be equal to or greater than 0.50, as the construct must account for more than half of the variance of its indicators (Hair et al., 2022).

By means of SmartPLS 4.1, this study completed the AVE measures of all constructs (see Table 4.7 above). In accordance with the results depicted in Table 4.7, the AVE values of the relevant constructs are between 0.649 and 0.776, matching up to the standard put forward by Hair et al. (2022) that AVE ought to be equal to or above 0.50, it suggested that at least 50 percent of the variance of the items is accounted for by the construct. As a conclusion, it can be revealed that the sample data of this investigation exhibited a good level of convergent validity.

4.5.4 Discriminant Validity

The last procedure of evaluating the reflective measurement model is the assessment of discriminant validity. As argued previously, the current study employs HTMT to evaluate discriminant validity (Henseler et al., 2015; Hair et al., 2022). All the constructs of the present study, including web drama audience satisfaction, web

drama viewing motivation, web drama exposure, audience social media engagement, and social media community size, are conceptually different constructs. Based on the argument from Henseler et al. (2015) and Hair et al. (2022), supposing that the HTMT value is less than 0.85 for conceptually different constructs, the researcher is able to determine that the discriminant validity of sample data is sufficient in the measurement model. Applying SmartPLS 4.1, the present research conducted the evaluation of discriminant validity, achieving the consequences showed in Table 4.8 below.

Table 4.8

Test Results of Discriminant Validity Based on HTMT for the Measurement Model

	AS	SMCS	SME	VM	WDE	SMCS × WDE
SMCS	0.513					
SME	0.752	0.560				
VM	0.653	0.357	0.583			
WDE	0.745	0.422	0.807	0.561		
SMCS × WDE	0.093	0.067	0.175	0.071	0.222	
SMCS × VM	0.132	0.061	0.061	0.030	0.079	0.437

Table 4.8 above presents the discriminant validity outcomes based on HTMT, which range from 0.03 to 0.807. After comparing the HTMT results for the 21 pairs of constructs with the threshold values proposed by Henseler et al. (2015) and Hair et al. (2022), this study found that none of the 21 comparisons violate the 0.85 criterion, indicating that discriminant validity for all constructs is adequate. In summary, the reflective measurement model of this study is confirmed through assessments of indicator reliability, internal consistency reliability, convergent validity, and

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discriminant validity. Meanwhile, these results indicate that the PLS-SEM algorithm used in this study to calculate construct scores is appropriate. Therefore, the subsequent evaluation of the structural model can proceed in the following analysis.

4.6 Hypothesis Testing Using PLS-SEM

After confirming that the measurement model is reliable and valid based on the assessment, this study proceeded to the second step of conducting PLS-SEM, which involves evaluating the structural model (Hair et al., 2019b; Hair et al., 2022), to examine the eleven hypotheses proposed in this study. Accordingly, this section covers the evaluation of the structural model, the test results of the direct relationships, and the analyses of the mediating and moderating effects. These three components are presented sequentially below.

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4.6.1 Assessment of the Structural Model

On the basis of the explanation from Hair et al. (2022), the precise procedures for evaluating structural model outcomes contain the assessment of the structural model for potential collinearity issues, the evaluation of the significance and relevance of the structural model relationships, the assessment of the model's explanatory capabilities, and the evaluation of the model's predictive capabilities. They are undertaken sequentially below.

4.6.1.1 Assessment of the Structural Model for Potential Collinearity Issues

As has been argued before, VIF value is adopted to complete the assessment of the structural model for potential collinearity issues (Atoyebi & Obilade, 2024; Hair et al., 2022; Suhayat et al., 2023). In light of the statement from Hair et al. (2022), the criterion of VIF value validating the absence of substantial effect of collinearity is that it is supposed to be less than 5, and ideally less than 3. Utilizing SmartPLS 4.1, the present research achieved the VIF values in the structural model, which are presented in Table 4.9 below.

Table 4.9

Test Results of Collinearity in the Structural Model

	AS	SME	WDE
SMCS	1.427	1.273	
SME	2.696		
VM	1.472	1.394	1.000
WDE	2.303	1.573	
SMCS × WDE		1.076	
SMCS × VM	1.023		

Table 4.9 presents the VIF values for all combinations of endogenous variables (columns) and their corresponding exogenous variables (rows). Specifically, it displays the following sets of predictors to assess multicollinearity. First, social media community size, audience social media engagement, web drama viewing motivation, web drama exposure, and social media community size × web drama viewing motivation as predictors of web drama audience satisfaction. Second, social media community size, web drama viewing motivation, web drama exposure, and

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social media community size × web drama exposure as predictors of audience social media engagement. Third, web drama viewing motivation as a predictor of web drama exposure.

In light of the test results exhibited in Table 4.9 above, the VIF values in the structural model are between 1 and 2.696. Now that every VIF value is smaller than 3 which is characterized as ideal (Hair et al., 2022) and there is no critical threshold of collinearity, the collinearity was deemed to have no significant impact on the estimations of the structural model. On the basis of this result, this research proceeded to the evaluation of the significance and relevance of the structural model relationships.

4.6.1.2 Evaluation of the Significance and Relevance of Structural Model Relationships

The hypothesized relationships among the constructs are represented by the path coefficients, which designate the structural model relationships (Faraz et al., 2021; Hair et al., 2022; Kumari, 2020; Ma et al., 2021). Referring to the statement from Hair et al., (2022), the present study utilized bootstrap confidence intervals to assess the significance of path coefficients. Supposing that zero value is excluded from a confidence interval for an estimated coefficient, the investigators may conclude that there is a significant effect (Hair et al., 2022).

In the meantime, Hair et al. (2022) highlight that the investigators are required to utilize *t* values, *p* values, or the bootstrap confidence intervals to examine the significance of all the associations in the structural model when analyzing the outcomes of a path model. According to Hair et al. (2019b) and Hair et al. (2022), the common criterion of *t* value is that, when *t* value is greater than 1.65 (10% significance level), or 1.96 (5% significance level), or 2.57 (1% significance level) for a two-tailed test, the structural model relationships are significant. As has been stated earlier, this study employs the 5% significance level, thus, whether *t* value is greater than 1.96 or whether *p* value is less than 0.05 can be adopted to assess the significance of the structural model relationships in the present investigation.

Meanwhile, Hair et al. (2022) remind the investigators that one of these testing outcomes is adequate for the sake of preventing reporting a large amount of redundant information. Furthermore, Hair et al. (2022) highlight that, the investigators are recommended to report the test results of the bootstrap confidence intervals due to that it is able to offer supplementary detail on the stability of coefficient estimates. Integrating all these suggestions above, this study decides to report *t* values, *p* values, and the bootstrap confidence intervals simultaneously in the table for the purpose of comprehensive showcasing the corresponding test results, and only analyze and discuss the outcomes of bootstrap confidence intervals in order to avoid excessive statements of redundant information.

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In PLS-SEM analytics, the significance of path coefficient is adopted to test the direct hypothesis of exogenous and endogenous latent variable (Hair et al., 2022). As has been proposed in Chapter Two, there are six direct hypotheses proposed that are in line with the first research question and the first six research objects in this study. They are summarized as follows:

H1: Web drama viewing motivation affects web drama audience satisfaction.

H2: Web drama viewing motivation has an impact on web drama exposure.

H3: Web drama exposure influences web drama audience satisfaction.

H4: Web drama viewing motivation impacts on audience social media engagement.

H5: Audience social media engagement affects web drama audience satisfaction.

H6: Web drama exposure has an influence on audience social media engagement.

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Based on the six direct hypotheses outlined above, this study estimated the path coefficients and their 95% confidence intervals for the related variables using SmartPLS 4.1. The analysis was conducted with the percentile bootstrap method, a 5% significance level, 20,000 bootstrap subsamples, a fixed seed, and a two-tailed test to assess the statistical significance of the six hypothesized relationships (Becker et al., 2023; Cheah et al., 2023a; Hair et al., 2022). The results are presented in Table 4.10 below.

Table 4.10

Path Coefficients and Their 95% Confidence Intervals of the Structural Model

Relationship	Path Coefficient	t-value	p-value	95% CI
VM -> AS	0.264	5.934	0.000	[0.177, 0.353]
VM -> WDE	0.511	12.549	0.000	[0.431, 0.590]
WDE -> AS	0.288	5.399	0.000	[0.184, 0.393]
VM -> SME	0.164	3.837	0.000	[0.079, 0.247]
SME -> AS	0.245	3.987	0.000	[0.124, 0.365]
WDE -> SME	0.530	12.570	0.000	[0.448, 0.613]

Table 4.10 above illustrates the path coefficients and their 95% confidence intervals of the structural model. Among the factors that directly influence web drama audience satisfaction, web drama exposure (0.288) possesses the greatest value of path coefficient, followed by web drama viewing motivation (0.264), while audience social media engagement (0.245) has the lowest path coefficient. More importantly, this research revealed that the values of 95% confidence intervals of all the direct relationships were without comprising zero value. It demonstrated that all the structural model relationships of this study were statistically significant.

Following the evaluation of the significance of structural model relationships, the current investigation concentrated on the assessment of the relevance of structural model relationships, implementing this evaluation by comparing the respective magnitudes of path coefficients (Hair et al., 2022; Manley et al., 2020). Concretely, the exogenous variable exhibiting the higher path coefficient exerts the more substantial influence on the endogenous variable and ought to be characterized as an

important construct for elucidating the endogenous variable (Hair et al., 2022; Manley et al., 2020). On the contrary, the exogenous variable with the lower path coefficient, despite its significance, does not demand the great attention from the investigators (Hair et al., 2022; Manley et al., 2020). By virtue of SmartPLS 4.1, the current research displays the structural model of this study in Figure 4.4 below.

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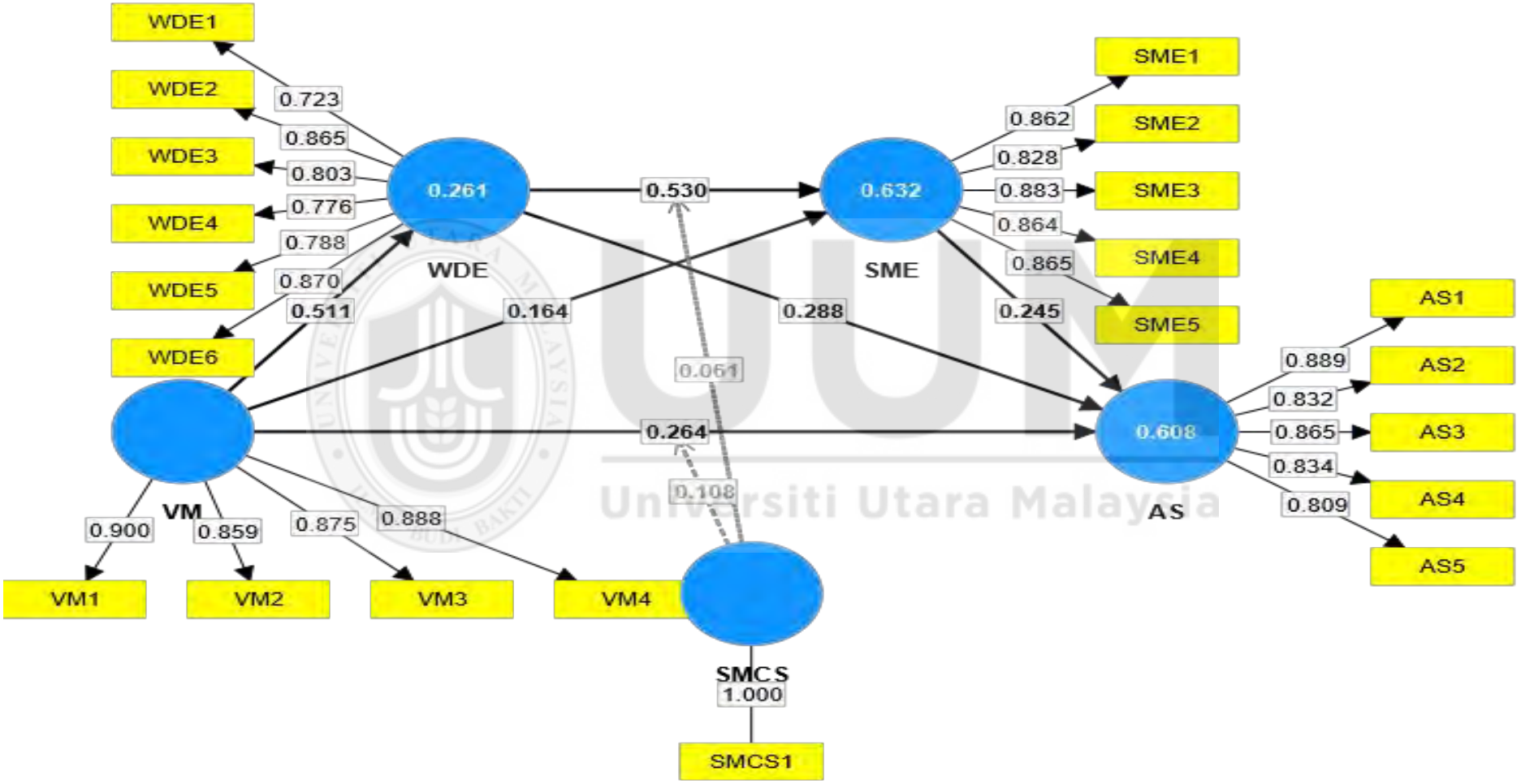


Figure 4.4 The Structural Model of the Study

Among the six direct relationships, web drama exposure (0.530) presents the highest path coefficient for audience social media engagement, followed by the relationship between web drama viewing motivation and web drama exposure (0.511). In addition, the differences in the path coefficient values of the other four pairs of direct associations are relatively small (0.288, 0.264, 0.245, 0.164), thus all the direct relationships of this study ought to be taken seriously in accordance with the outcomes manifested in Table 4.10 above and Figure 4.4 above.

4.6.1.3 Assessment of the Model's Explanatory Capabilities

As outlined above, the present study utilizes R^2 values to appraise the explanatory power of the structural model, the greater R^2 values means the higher levels of explanatory power (Hair et al., 2022). R^2 values of 0.75, 0.50, and 0.25 are considered as substantial, moderate, and weak on the basis of the guideline (Hair et al., 2019a). Employing SmartPLS 4.1, this study achieved the R^2 values of all endogenous latent variables, which are depicted in Table 4.11 below.

Table 4.11

R^2 Measurement of All Endogenous Latent Variables

Endogenous Variable	R^2 value
AS	0.608
WDE	0.261
SME	0.632

From Figure 4.11 above, it can be discovered that audience social media engagement (R^2 = 0.632) possesses the highest level of explanatory capability among the three

endogenous variables, followed by web drama audience satisfaction (0.608). The endogenous variable with the lowest level of explanatory power is web drama exposure ($R^2 = 0.261$). Furthermore, both the explanatory powers of audience social media engagement ($R^2 = 0.632$) and web drama audience satisfaction (0.608) are between substantial and moderate, while the explanatory capability of web drama exposure ($R^2 = 0.261$) falls between moderate and weak. The R^2 values of audience social media engagement ($R^2 = 0.632$) and web drama audience satisfaction ($R^2 = 0.608$) underscores the model's relatively robust explanatory capability. Meanwhile, it is the deficiency of this study that web drama exposure ($R^2 = 0.261$) is close to the weak explanatory power.

Besides that, the investigators can utilize R^2 value to measure how strong the structural model relationships are by virtue of f^2 effect size (Becker et al., 2023; Cohen, 2013; Hair et al., 2022). The f^2 effect size denotes the modification in the R^2 value that occurs when a certain predecessor construct is excluded from the model (Chin, 2009; Cohen, 2013; Hair et al., 2022). The criteria for evaluating f^2 effect size are that the values of 0.02, 0.15, and 0.35 separately correspond to small, medium, and large effects of the exogenous variable, the result of it can indicate to what extent an exogenous construct can play a role in understanding an endogenous construct, the f^2 effect size values below 0.02 signify the absence of a measurable effect (Becker et al., 2023; Cohen, 2013; Hair et al., 2022). Table 4.12 below illustrates the the f^2 effect sizes of the latent constructs of this study.

Table 4.12

f² Effect Sizes of the Latent Constructs of the Study

Relationship	f² value	Decision
VM -> WDE	0.354	Large
VM -> SME	0.053	Small
WDE -> SME	0.486	Large
SMCS -> SME	0.150	Medium
VM -> AS	0.121	Small
WDE -> AS	0.092	Small
SME -> AS	0.057	Small
SMCS -> AS	0.043	Small

Table 4.12 above shows that all the f² values for the latent constructs in this study exceed 0.02, indicating measurable effects of all exogenous constructs. Specifically, with respect to web drama exposure, only the exogenous construct of web drama viewing motivation exhibits a large effect size. Regarding audience social media engagement, web drama exposure has a large effect, social media community size has a medium effect, and web drama viewing motivation has a small effect. In terms of web drama audience satisfaction, all exogenous constructs, including web drama viewing motivation, web drama exposure, audience social media engagement, and social media community size, exhibit only small effects.

4.6.1.4 Evaluation of the Model's Predictive Capabilities

As has been noted before, the present research applies the $PLS_{predict}$ procedure that serves as the primary approach for assessing the predictive capability of the PLS path model (Shmueli et al., 2016; Hair et al., 2022). Following the recommendations from

Hair et al. (2022), this study implemented the $PLS_{predict}$ procedure. In the initial process, the $PLS_{predict}$ procedure was executed with 10 folds and 10 repetitions for the purpose of achieving the $PLS_{predict}$ result report, which is exhibited in Table 4.12 below. In Table 4.13 below, this research revealed that the $Q^2_{predict}$ values of all the corresponding indicators are more than zero, it indicated that the prediction error from the PLS path model is inferior to that of the most naïve benchmark, in other words, the PLS path model surpasses the most naïve benchmark (Hair et al., 2022).

Table 4.13

$PLS_{predict}$ Result Report of the PLS Path Model

Constructs	Attributes	RMSE generated by PLS-SEM	$Q^2_{predict}$
AS	AS1	0.783	0.388
	AS2	0.840	0.297
	AS3	0.845	0.288
	AS4	0.844	0.290
	AS5	0.842	0.293
WDE	WDE1	0.918	0.159
	WDE2	0.934	0.132
	WDE3	0.940	0.120
	WDE4	0.877	0.234
	WDE5	0.930	0.138
	WDE6	0.911	0.174
SME	SME1	0.829	0.315
	SME2	0.852	0.276
	SME3	0.831	0.310
	SME4	0.822	0.326
	SME5	0.860	0.262

Therefore, the present analysis proceeded to compare the RMSE values generated by the PLS-SEM analysis with those from the naïve LM benchmark model; the

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comparison results are presented in Table 4.14 below. It should be noted that, according to Hair et al. (2022), researchers should identify a key target construct in the PLS path model to assess its predictive performance. In this study, web drama audience satisfaction was selected as the target construct for this comparative evaluation.

Table 4.14

Comparison of Distinct RMSE Values from PLS and LM

Construct	Attributes	RMSE value from PLS	RMSE value from LM
AS	AS1	0.783	0.797
	AS2	0.840	0.853
	AS3	0.845	0.852
	AS4	0.844	0.854
	AS5	0.842	0.859

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Based on the results displayed in Table 4.14 above, this study found that the RMSE values for all indicators of web drama audience satisfaction in the PLS-SEM analysis are lower than those from the naïve LM benchmark model. This indicates that the proposed model exhibits high predictive capability.

4.6.2 Test Results of Direct Relationships

The direct relationships in SEM represent the direct effects between exogenous and endogenous latent variables (Kline, 2023). Based on the analytical results regarding the significance of path coefficients in the structural model, as presented in Table 4.10 above, this study determines whether to support or reject the six direct hypotheses, which are discussed in the following sections in sequential order.

To begin with, the consequences in Table 4.10 above display that there is a significant direct and positive relationship between web drama viewing motivation and web drama audience satisfaction (β = 0.264, 95% CI = [0.177, 0.353]). It suggested that web drama audience satisfaction is directly impacted by web drama viewing motivation. As a consequence, the hypothesis 1 held. Followed by that, the results revealed that web drama viewing motivation significantly and positively impacts web drama exposure (β = 0.511, 95% CI = [0.431, 0.590]). It signified that, the stronger viewing motivation from web drama audience, the more exposure to web drama. Therefore, the hypothesis 2 was supported.

Moreover, a significant and positive association exists between web drama exposure and web drama audience satisfaction (β = 0.288, 95% CI = [0.184, 0.393]). It indicates that web drama exposure has a positive influence on web drama audience satisfaction. As a result, the hypothesis 3 held. Furthermore, the outcomes manifested that audience social media engagement is directly and positively affected by web drama viewing motivation (β = 0.164, 95% CI = [0.079, 0.247]). It meant that, the stronger viewing motivation from web drama audience, the more engagement from them on social media. Thus, the hypothesis 4 was supported.

Next, it can be discovered that there exists a significant and positive association between audience social media engagement and web drama audience satisfaction (β

= 0.245, 95% CI = [0.124, 0.365]). To be specific, social media engagement from web drama audience has a positive impact on web drama audience satisfaction. Consequently, the hypothesis 5 held. On top of that, an additional outcome was that web drama exposure from audience significantly and positively influences audience social media engagement (β = 0.530, 95% CI = [0.448, 0.613]). In other words, the more web drama exposure from audience, the more social media engagement from web drama audience. Accordingly, the hypothesis 6 was supported.

Meanwhile, on the basis of the consequences of path coefficients in Table 4.10 above, the strongest relationship is between web drama exposure and audience social media engagement among the six direct associations. While, web drama viewing motivation signifies the weakest relationship with audience social media engagement. Table 4.15 below illustrates the testing results of direct hypotheses.

Table 4.15

Test Results of Direct Hypotheses of the Study

No.	Hypothesis Statement	Status
H1	Web drama viewing motivation affects web drama audience satisfaction.	Supported
H2	Web drama viewing motivation affects web drama exposure.	Supported
H3	Web drama exposure affects web drama audience satisfaction.	Supported
H4	Web drama viewing motivation affects social media engagement.	Supported
H5	Social media engagement affects web drama audience satisfaction.	Supported
H6	Web drama exposure affects social media engagement.	Supported

4.6.3 Examinations of Mediating and Moderating Relationships

This study proposes three hypothesized mediating relationships corresponding to the second research question and the second set of research objectives, as well as two assumed moderating relationships aligned with the third research question and the third set of research objectives. These relationships are listed below.

H7: Web drama exposure mediates the relationship between web drama viewing motivation and web drama audience satisfaction.

H8: Audience social media engagement mediates the relationship between web drama viewing motivation and web drama audience satisfaction.

H9: Web drama viewing motivation are indirectly related to web drama audience satisfaction, sequentially mediated through web drama exposure and audience social media engagement.

H10: Social media community size moderates the direct effect of web drama viewing motivation on web drama audience satisfaction.

H11: Social media community size moderates the relationship between web drama exposure and audience social media engagement.

To test hypotheses 7–11, PLS-SEM was employed. For the mediation analysis, this study applied 95% bootstrap confidence intervals with the percentile method, 5% significance level, 20,000 bootstrap subsamples, fixed seed and the two-tailed test

(Becker et al., 2023; Cheah et al., 2023a; Hair et al., 2022). A mediating effect is considered statistically significant if the 95% bootstrap confidence interval for the indirect effect does not include zero (Hayes, 2009; Hair et al., 2022). In addition to bootstrap confidence intervals, *t* values and *p* values are manifested concurrently in the table of the present investigation. Nevertheless, only the results of the bootstrap confidence intervals are analyzed and discussed in order to prevent overly redundant statements according to Hair et al. (2022).

In terms of the examination of moderating relationship, the present study investigated the interaction term's significance by virtue of bootstrapping in the PLS path model (Hair et al., 2022). More specifically, the present investigation still utilize 95% bootstrap confidence intervals adopting the percentile method, 5% significance level, 20,000 bootstrap subsamples, fixed seed and the two-tailed test (Becker et al., 2023; Cheah et al., 2023a; Hair et al., 2022). In the event that the 95% bootstrap confidence interval for the interaction term's effect does not include zero, the researchers can reveal that the interaction effect is significant, hence indicating the existence of a moderating effect.

Moreover, in the analysis of the interaction term's effect, this research is required to investigate the f^2 effect size of the interaction term (Becker et al., 2023; Hair et al., 2022). Besides that, the simple slope analysis is employed to evaluate the moderating degree in this investigation (Hair et al., 2022; Latan et al., 2023). The test results of

the mediating relationships and the moderating relationships are argued in the following statement.

4.6.3.1 Web Drama Viewing Motivation and Web Drama Audience Satisfaction: Testing Web Drama Exposure as Mediator

Regarding Hypothesis 7, this study examined the mediating effect of web drama exposure in the relationship between web drama viewing motivation and web drama audience satisfaction using SmartPLS 4.1. The results are presented in Table 4.16 below. There exist two indications in Table 4.16 below, one is that zero is not between the lower and upper bound of 95% confidence interval (95% CI = [0.092, 0.209]), as a conclusion, it signified that the mediating effect of web drama exposure in the relationship between those two constructs is existent. The other is that web drama audience satisfaction is indirectly affected by web drama viewing motivation through web drama exposure. Furthermore, given that the path coefficient from web drama viewing motivation to web drama audience satisfaction is significant (see Table 4.10), this mediating effect is partial (Hair et al. 2019b). Accordingly, the hypothesis 7 was supported.

4.6.3.2 Web Drama Viewing Motivation and web drama audience satisfaction: Testing Web Drama Audience's Social Media Engagement as Mediator

Confronted with hypothesis 8, the present research also employ bootstrap confidence intervals to test whether audience social media engagement plays a mediating role in

the association between web drama viewing motivation and web drama audience satisfaction. After undertaking the relevant calculation, this study achieved the test results displayed in Table 4.16 below.

Based on the consequences of this test manifested in Table 4.16 below, this study revealed that the 95% confidence intervals exclude zero (95% CI = [0.014, 0.073]). It demonstrates that the relationship between web drama viewing motivation and web drama audience satisfaction is mediated by audience social media engagement. Moreover, on the basis of the outcomes depicted in Table 4.16 below, it can be discovered that web drama viewing motivation has an indirect influence on web drama audience satisfaction through audience social media engagement. Furthermore, considering that the path coefficient from web drama viewing motivation to web drama audience satisfaction is significant (see Table 4.10), the current study can claim that audience social media engagement partially mediates the association between web drama viewing motivation and web drama audience satisfaction (Hair et al. 2019b). Thus, the hypothesis 8 held.

4.6.3.3 Web Drama Viewing Motivation and web drama audience satisfaction: Testing Web Drama Exposure and Audience Social Media Engagement as Serial Mediators

In response to Hypothesis 9, the present study performed the assessment of serial mediating effect of web drama exposure and audience social media engagement as

serial mediators in the direct relationship between web drama viewing motivation and web drama audience satisfaction. The serial mediators are characterized as the two or more mediating variables that sequentially mediate exogenous and endogenous variables (Akdoğan & Çimşir, 2019; He et al., 2022; Yue et al., 2023) and generate the serial mediating effect (Hair et al., 2022). Likewise, bootstrap confidence intervals were utilized to accomplish the examination of this serial mediating effect by means of SmartPLS 4.1. Table 4.16 below manifests the final outcome.

Table 4.16 below presents that the 95% confidence intervals are without zero (95% CI = [0.033, 0.104]), it meant that as serial mediators, web drama exposure and audience social media engagement sequentially mediate the relationship between web drama viewing motivation and web drama audience satisfaction. In addition, according to Table 4.16 below, the present research found that web drama viewing motivation indirectly impacts web drama audience satisfaction through the sequential mediating effects of web drama exposure and audience social media engagement. On top of that, given that the path coefficient from web drama viewing motivation to web drama audience satisfaction is significant (see Table 4.10), the current study can announce that the relationship between web drama viewing motivation and web drama audience satisfaction is partially mediated by web drama exposure and audience social media engagement as serial mediators (Hair et al., 2019b). Thus, the results of this investigation supported the hypothesis 9.

Table 4.16

Test Results of Mediating Relationship of the Study

Mediating Relationship	t-value	p-value	95% CI
VM -> WDE -> AS	4.957	0.000	[0.092, 0.209]
VM -> SME -> AS	2.651	0.008	[0.014, 0.073]
VM -> WDE -> SME -> AS	3.696	0.000	[0.033, 0.104]

4.6.3.4 Direct Relationship between Web Drama Viewing Motivation and web drama audience satisfaction: Testing Social Media Community Size as Moderator

With respect to Hypothesis 10, this study employed bootstrapping to test the significance of the interaction term in order to examine the moderating effect of social media community size in the direct relationship between web drama viewing motivation and web drama audience satisfaction, using SmartPLS 4.1. After conducting the corresponding computations, the study obtained the 95% bootstrap confidence interval for the effect of the interaction term, as displayed in Table 4.16 below.

Table 4.16 below manifests that the 95% bootstrap confidence interval for the effect of interaction term (SMCS × VM) does not include zero (95% CI = [0.002, 0.195]), the researchers can reveal that the effect of interaction term (SMCS × VM) is significant, hence indicating the existence of the significant moderating effect of social media community size on the direct relationship between web drama viewing

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motivation and web drama audience satisfaction. As a conclusion, the present investigation supported the Hypothesis 10.

Furthermore, based on Figure 4.4 above, the path coefficient of social media community size moderating the direct relationship between web drama viewing motivation and web drama audience satisfaction is positive (β = 0.108), therefore, it can be discovered that the direct relationship between web drama viewing motivation and web drama audience satisfaction is positively moderated by social media community size. Additionally, following accomplishing the simple slope analysis, this investigation illustrates simple slope plot of moderating effect of social media community size in the direct relationship between web drama viewing motivation and web drama audience satisfaction in Figure 4.5 below.

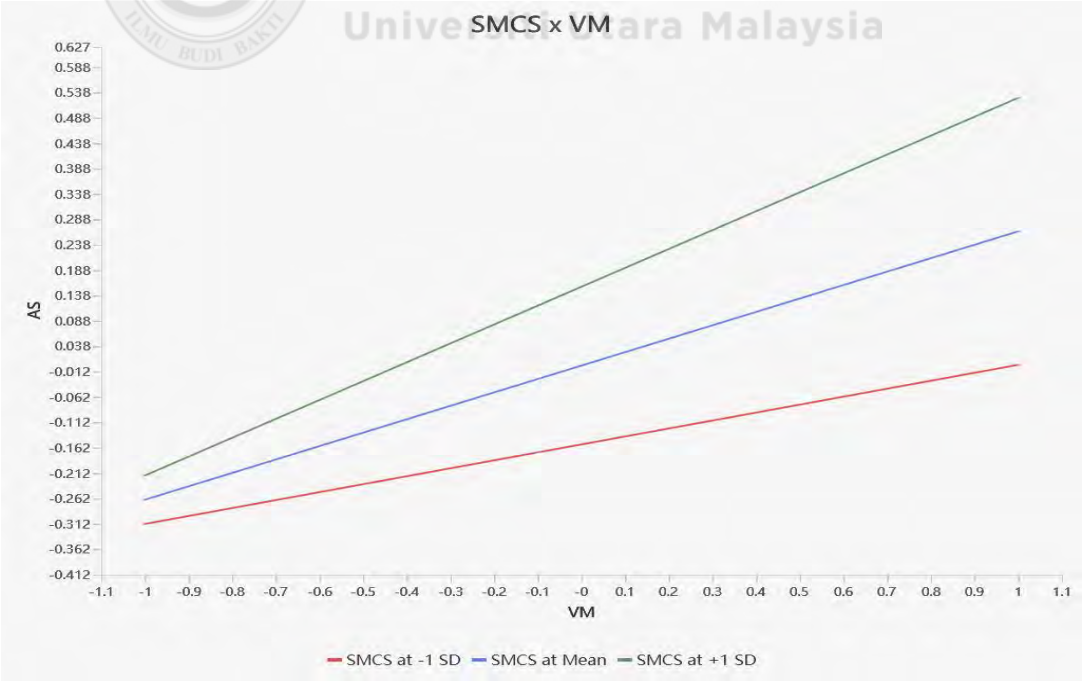


Figure 4.5 Simple Slope Plot (SMCS × VM)

As shown in Figure 4.5, the relationship between web drama viewing motivation and web drama audience satisfaction is stronger when the level of the moderator, social media community size, is high (see green line), and weaker when the level of the moderator is low (see red line). This result indicates a positive moderating effect of social media community size on the direct relationship between web drama viewing motivation and web drama audience satisfaction.

On top of that, the f^2 value of the interaction term (SMCS × VM) is 0.029 according to Table 4.16, it signifies that the interaction term (SMCS × VM) possesses large effect size (Becker et al., 2023; Hair et al., 2022; Hair et al., 2021). As a result, it can be confirmed that this moderating effect is substantial (Becker et al., 2023).

4.6.3.5 Web Drama Exposure and Audience Social Media Engagement: Testing Social Media Community Size as Moderator

With respect to Hypothesis 11, to examine the moderating effect of social media community size on the relationship between web drama exposure and audience social media engagement, this study conducted a significance test of the interaction term using bootstrapping in SmartPLS 4.1. The results of the test are presented in Table 4.16 below. As shown in Table 4.17, the effect of the interaction term on audience social media engagement is statistically significant (95% CI = [0.008, 0.115]). This indicates that the relationship between web drama exposure and audience social

media engagement is significantly moderated by social media community size. Therefore, the current study supports Hypothesis 11.

To further clarify the moderating role, given that the path coefficient for social media community size in moderating the relationship between web drama exposure and audience social media engagement is positive (β = 0.061), as shown in Figure 4.4 above, the present study confirms that social media community size positively moderates this relationship. Furthermore, after conducting the simple slope analysis, the current research presents the simple slope plot illustrating the moderating effect of social media community size on the relationship between web drama exposure and audience social media engagement, as displayed in Figure 4.6 below.

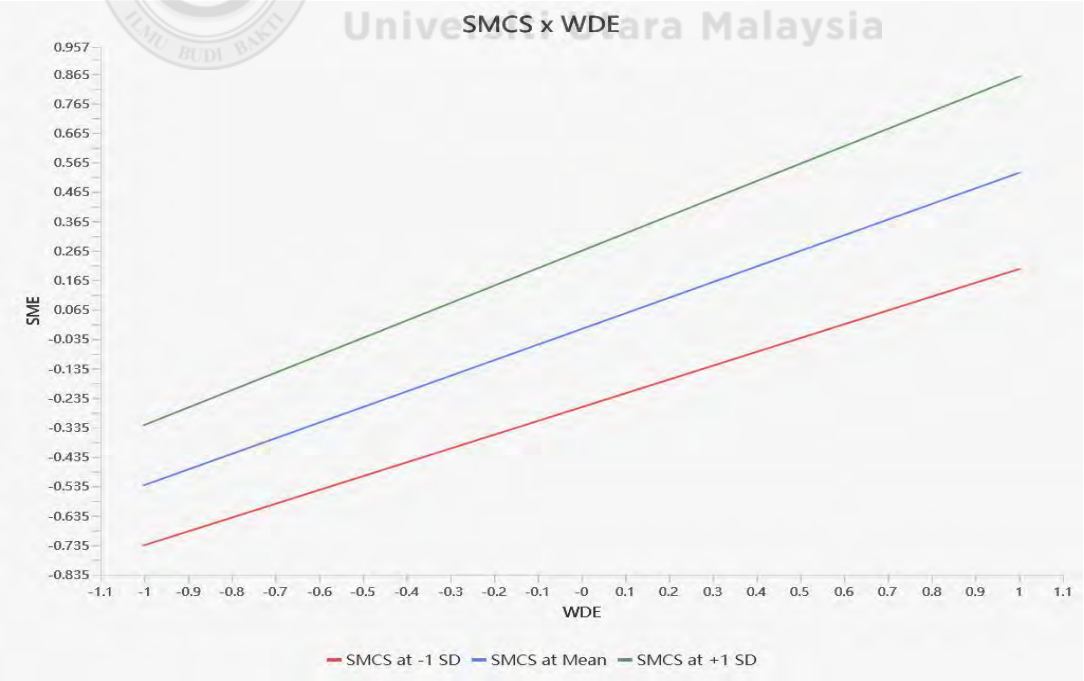


Figure 4.6 Simple Slope Plot (SMCS × WDE)

Based on Figure 4.6 above, the relationship between WDE and SME becomes stronger under high levels of the moderator SMCS, as indicated by the green line. Conversely, the association between WDE and SME weakens when SMCS levels are low, as shown by the red line. In summary, these results confirm that social media community size positively moderates the relationship between web drama exposure and audience social media engagement.

Table 4.17

Test Results of Moderating Relationship of the Study

Moderating Relationship	t-value	p-value	f^2	95% CI
SMCS × VM -> AS	2.141	0.032	0.029	[0.002, 0.195]
SMCS × WDE -> SME	2.256	0.024	0.011	[0.008, 0.115]

In addition, after examining the interaction term (SMCS × WDE), the current study reveals a medium effect size, as indicated by an f^2 value of 0.011 (Becker et al., 2023; Hair et al., 2022; Hair et al., 2021), which is presented in Table 4.17 above. Therefore, the moderating effect can be considered substantial (Becker et al., 2023).

After examining the mediating and moderating relationships, the present study summarizes the results for Hypotheses 7 through 11, as illustrated in Table 4.18 below.

Table 4.18

Test Results of Mediating and Moderating Hypotheses of the Study

No.	Hypothesis Statement	Status
H7	Web drama exposure mediates the relationship between web drama viewing motivation and web drama audience satisfaction.	Supported
H8	Audience social media engagement mediates the relationship between web drama viewing motivation and web drama audience satisfaction.	Supported
H9	Web drama viewing motivation are indirectly related to web drama audience satisfaction, sequentially mediated through web drama exposure and audience social media engagement.	Supported
H10	Social media community size moderates the direct effect of web drama viewing motivation on web drama audience satisfaction.	Supported
H11	Social media community size moderates the relationship between web drama exposure and audience social media engagement.	Supported

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4.7 Achievement of Research Questions and Objectives

4.7.1 Answers to the Research Questions

Building on the research aim detailed in Chapter One, this study formulated four research questions. The first research question examined the direct relationships among the four primary constructs, specifically investigating whether direct effects exist between web drama audience satisfaction, web drama viewing motivation, web drama exposure, and audience social media engagement.

The second and third research questions pertain to mediating and moderating associations. Specifically, the second research question examines whether web drama exposure and audience social media engagement mediate the relationship between

web drama viewing motivation and audience satisfaction. Additionally, the third research question investigates whether social media community size moderates the direct relationship between web drama viewing motivation and audience satisfaction, as well as the association between web drama exposure and audience social media engagement.

The fourth research question falls within the domain of exploratory research (Babbie, 2020; Boyle & Schmierbach, 2024). It explores whether web drama viewing motivation, web drama exposure, audience social media engagement, and social media community size are significant antecedents in the predictive modeling of audience satisfaction in Chinese web dramas.

In Chapter Two, the first six hypotheses were formulated to address the first research question, while the subsequent three hypotheses were developed in relation to the second research question. The final two hypotheses, corresponding to the third research question, were also proposed. Based on the test results for the direct, mediating, and moderating effects presented in Tables 4.15 and 4.18, the present study confirms that all eleven hypotheses are supported. These findings provide affirmative answers to the first three research questions raised in Chapter One.

In addressing the fourth research question, which was exploratory in nature, no predetermined hypothesis was formulated (Haile, 2023). However, insights into this

question can be derived from the hypotheses supported by the study. Specifically, all hypotheses are empirically supported by the research findings, revealing six direct effects among web drama audience satisfaction, web drama viewing motivation, web drama exposure, and audience social media engagement, as well as the mediating roles of web drama exposure and audience social media engagement, and the moderating effect of social media community size.

Therefore, this study confirms that web drama viewing motivation, web drama exposure, audience social media engagement, and social media community size are significant antecedents in developing a predictive model of audience satisfaction in Chinese web dramas. Consequently, the fourth research question is affirmatively answered, providing a robust foundation for the development of such a predictive model.

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4.7.2 Accomplishment of Research Objectives

In Chapter One, the four research objectives were formulated to address the four research questions in sequential order. Specifically, the first research objective was to examine the direct relationships among web drama viewing motivation, web drama exposure, audience social media engagement, and web drama audience satisfaction. The second research objective attempts to investigate the mediating effects of web drama exposure and audience social media engagement in the relationship between web drama viewing motivation and audience satisfaction.

The third research objective sought to assess the moderating effect of social media community size on both the direct relationship between web drama viewing motivation and audience satisfaction and the association between web drama exposure and audience social media engagement. Finally, in response to the fourth research question, the fourth research objective was to determine whether web drama viewing motivation, web drama exposure, audience social media engagement, and social media community size are significant antecedents in the development of a predictive model for audience satisfaction in Chinese web dramas.

The confirmation of the eleven hypotheses in this study indicates the achievement of the research objectives. Specifically, support for hypotheses 1 through 6, which examined direct relationships, demonstrates the accomplishment of the first research objective. Additionally, the acceptance of hypotheses 7, 8, and 9 reflects the fulfillment of the second research objective. Similarly, the empirical support for hypotheses 10 and 11 confirms the attainment of the third research objective. Finally, the overall validation of all hypotheses provides evidence for the achievement of the fourth research objective.

In addition, since the overall research objectives were derived from the research questions and exhibited a precise correspondence with them, they could be achieved through effective responses to the respective research questions. Given that all

research questions were successfully answered, the overall research objectives were thus accomplished.

4.8 Application of the Predictive Model

This study aims to establish a comprehensive predictive model of audience satisfaction in Chinese web dramas grounded in the theoretical frameworks of UGT and CCT through a big data analytics approach. Based on the test results presented above, the research confirms the eleven proposed hypotheses, thereby achieving all four research objectives. This outcome validates the hypothesized predictive model (see Figure 2.3). Given the practical value and applicability of this model, the following section applies it to predict audience satisfaction levels for recent Chinese web dramas, demonstrating the model's practical utility and effectiveness.

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According to Boyle and Schmierbach (2024), the application focuses on addressing concrete issues by facilitating practical solutions to naturally occurring situations, including market research, public relations, broadcasting, and advertising. Meanwhile, Babbie (2020) underscores the importance of theory in practical applications, noting that social research has numerous applied uses. In communication research, increasing attention has been paid in recent years to the application of communication theories (Gupta et al., 2021; Harrington & Record, 2023; Yu et al., 2022). Consequently, the application of the predictive model

developed in this study to forecast audience satisfaction holds significant practical value in the context of Chinese web dramas.

4.8.1 Establishment of the Predictive Equation Based on the Predictive Model

To enable an accurate comparison of predicted outcomes across differential web dramas, this study seeks to develop a predictive equation based on the comprehensive predictive model through SPSS PROCESS 4.2. As a user-friendly and complementary tool for SPSS, PROCESS facilitates the implementation of mediation, moderation, and conditional process analyses (Hayes, 2022; Hayes et al., 2017; Igartua & Hayes, 2021). It employs ordinary least squares regression to estimate model parameters (Hayes, 2022; Hayes et al., 2017; Igartua & Hayes, 2021).

More importantly, SPSS PROCESS 4.2 offers certain advantages that SmartPLS 4.1 does not possess. Specifically, it provides unstandardized regression coefficients for the relevant variables as well as the corresponding constant values (Hayes, 2022; Hayes et al., 2017; Igartua & Hayes, 2021). Moreover, it enables the integration of parameter estimates across at least two model equations in mediation and conditional process analyses (Hayes, 2022; Hayes et al., 2017; Igartua & Hayes, 2021). Therefore, this study employs SPSS PROCESS 4.2 to construct the predictive equation based on the proposed predictive model, facilitating efficient and convenient prediction.

This study adopted a two-stage approach to develop the prediction equation. The first stage involved categorizing the moderating variable into high-level and low-level groups, while the second stage entailed constructing separate prediction equations for each group using SPSS PROCESS 4.2. Regarding the initial stage, according to Hair et al. (2022), researchers can use a categorical moderator to divide the sample data into multiple groups, enabling them to estimate the models separately for each group.

Drawing on this approach, this study implemented high and low grouping to separately estimate model parameters for each group of sample data and further formulate the prediction equation based on the models' estimation results. In other words, the study sought to transform the continuous moderator into a categorical variable and estimate separate models across categories. This approach enables an efficient and convenient derivation of the audience satisfaction prediction equation for Chinese web dramas.

More specifically, several procedures were conducted in the first stage. First, the original raw data of social media community size was tested to calculate its mean value. The present study obtained a mean of 104,170 for this moderator variable. Notably, high and low grouping must be based on the original raw values of the moderator, not on processed data. Subsequently, all 288 samples in this study were divided into two groups: a high-level group containing 139 samples and a low-level group comprising 149 samples, using the mean value of 104,170 as the threshold.

In the second stage, the current study separately imported sample data from the high-level and low-level groups into SPSS 29.0 to estimate the models for each group. After completing the estimation, the minimum required sample size for each group was assessed using G*Power 3.1.9.7. Following the selection of F tests, linear multiple regression: fixed model, R^2 deviation from zero, a priori: compute required sample size - given α, power, and effect size, f^2 effect size of 0.15, α level of 0.05, power value of 0.95, and 3 predictors (Bartlett, 2022; Chaokromthong & Sintao, 2021; Roni & Djajadikerta, 2021), the study obtained the sample size estimation result, as shown in Figure 4.7 below.

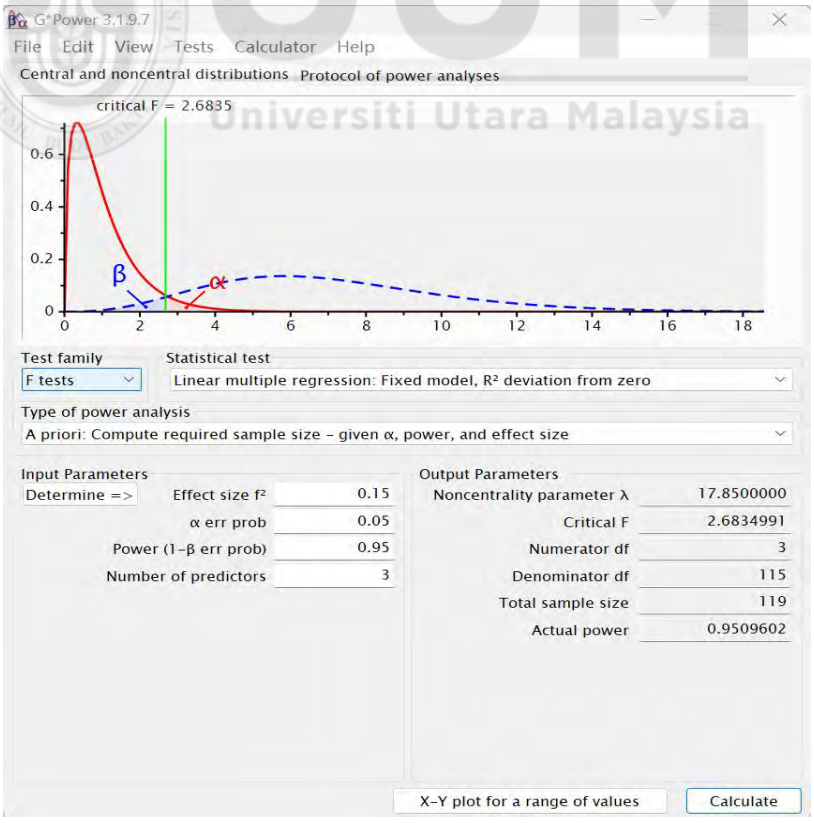


Figure 4.7 The Result of Sample Size Estimation for Each Group from G*Power 3.1.9.7

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According to Figure 4.7 above, the estimated sample size requirement for each group is 119. This indicates that both the high-level group (139 samples) and the low-level group (149 samples) meet the minimum sample size requirement. Therefore, the current study can separately estimate the models for the high-level and low-level groups using SPSS PROCESS 4.2.

When using SPSS PROCESS 4.2, the present study specified the model number, confidence level, and number of bootstrap samples. First, because the moderating variable was excluded, the remaining four variables form a multi-step multiple mediation model (Hayes, 2009), which corresponds to Model 6 in Hayes' s (2022) framework of mediation, moderation, and conditional process analysis. Therefore, Model 6 was selected as the model number. In addition, to maintain consistency with the SmartPLS 2.0 analysis, 95% confidence intervals and 20,000 bootstrap samples were applied in the execution of SPSS PROCESS 4.2. After setting these parameters, the study conducted the analysis using SPSS PROCESS 4.2 to obtain the estimation results for each group.

In accordance with Hayes (2022), the estimation results of Model 6 can illustrate the total effect of the independent variable on the dependent variable, which can be quantified by the independent variable' s regression coefficient when mediators are excluded from the model. More specifically, these results support the formulation of the Model 6 equation, as shown below:

$$Y = i + cX + e$$

Among them, Y is the dependent variable, i denotes the regression constant, c represents the regression coefficient associated with the independent variable, and e refers to the error in the estimation of Y (Hayes, 2022). Furthermore, Hayes (2022) notes that the estimation error is typically not regarded as a predictor of the outcome variable by researchers. Therefore, the equation for Model 6 can be reformulated and further expressed as follows:

$$Y = i + cX$$

Following that, this study was required to extract the value of the regression constant (i.e., the value of i in the equation) and the regression coefficient associated with the independent variable (i.e., the value of c in the equation) from the estimation results of Model 6. Following the separate estimation of the models for high-level and low-level groups using SPSS PROCESS 4.2, this study obtained distinct predictive equations for audience satisfaction in Chinese web dramas. These are presented below.

Predictive equation of high-level group (equation 1):

$$Y = 0.152102 + 0.688982*X$$

Predictive equation of low-level group (equation 2):

$$Y = -0.224433 + 0.328222*X$$

Building on the two prediction equations presented above, once researchers obtain the values of the viewing motivation variable through big data, they can effectively conduct satisfaction predictions.

4.8.2 Predicted Results of Recent Ten Chinese Web Dramas

After deriving the two predictive equations, the present study selected ten recent Chinese web dramas to predict audience satisfaction. First, this study randomly selected ten recent Chinese web dramas, as shown in Table 4.19 below. Among them, all but the ninth web drama have English titles. Therefore, the title of the ninth web drama is presented in Chinese pinyin, while the others are given in English.

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Table 4.19

Recent Ten Chinese Web Dramas Selected for Prediction

No.	Web Drama Title	Release Time
1	*Love Game in Eastern Fantasy*	November 1st, 2024
2	*Snowy Night Timeless Love*	October 9th, 2024
3	*Fangs of Fortune*	October 26th, 2024
4	*Kill Me Love Me*	October 14th, 2024
5	*Are You the One*	August 12th, 2024
6	*Go East*	August 23rd, 2024
7	*Twenty-One Days*	September 26th, 2024
8	*Duel of Shadows*	October 23rd, 2024
9	*Hun Yin Gong Lue* (Chinese pinyin)	August 29th, 2024
10	*The Vanished Elephant*	July 4th, 2024

Next, this study conducted big data crawling, collecting 438,537 comments from major Chinese social media platforms including Weibo, Douban, Zhihu, and Xiaohongshu using GooSeeker software. Following sentiment analysis performed with Miniconda, the study obtained the values of all attributes of web drama viewing motivation for the ten Chinese web dramas. Based on the study's statistical analysis procedure for big data, the collected values were subjected to logarithmic transformation and data normalization. Subsequently, the PLS-SEM algorithm was employed to calculate the construct scores of viewing motivation for the ten Chinese web drama samples. Speficically, these scores were derived by forming a linear combination of the indicators, using the outer loadings (as presented in Table 4.6) as weights.

Meanwhile, the values of social media community size for the ten Chinese web drama samples must be fully obtained. Specifically, this study extracted the numbers of fans on the official Weibo accounts of the ten Chinese web dramas as the values of social media community size. Notably, these values were retained in their original data form to accurately distinguish which samples belong to the high-level group and which to the low-level group. As previously stated, the mean value of social media community size (104,170) serves as the threshold distinguishing high-level from low-level groups. Accordingly, this study divided the ten Chinese web dramas into high-level and low-level groups based on the mean value of social media community

size (104,170), using distinct prediction equations to compute the predicted outcomes.

This study takes *Love Game in Eastern Fantasy* as an example to illustrate how the predicted results are derived from the predictive equation by substituting actual values. First, this study collected 78,530 comments on the web drama from Weibo, 49,960 from Douban, 644 from Zhihu, and 2,316 from Xiaohongshu using GooSeeker software. Following that, the study conducted sentiment analysis on these comments to identify and quantify those expressing viewing motivations toward a given web drama, thereby obtaining the values of all attributes of web drama viewing motivation for this web drama.

Upon calculation, the values of all these attributes were determined as follows: VM1 = 8546, VM2 = 8787, VM3 = 173, and VM4 = 186. Next, this study applied logarithmic transformation and data normalization to the collected values. The resulting transformed and normalized attribute values were as follows: VM1 = 1.0288, VM2 = 1.1975, VM3 = 1.5121, and VM4 = -0.9794. Subsequently, the value of the viewing motivation variable was derived by forming a linear combination of its indicators, using the outer loadings of these indicators (as presented in Table 4.6) as weights. Upon calculation, the value of the viewing motivation variable for the web drama *Love Game in Eastern Fantasy* was determined to be 2.408, as presented in Table 4.20 below.

Following that, this study retrieved the number of fans on the official Weibo accounts of this web drama, thereby obtaining the value of social media community size. Upon retrieval, the value of social media community size for this web drama was determined to be 722,000. As previously stated, the mean value of social media community size (104,170) serves as the threshold distinguishing high-level from low-level groups. Therefore, this web drama belongs to the high-level group and is suitable for the predictive equation for high-level groups (Equation 1), namely Y = 0.152102 + 0.688982×X. Accordingly, this study substituted the value of the viewing motivation variable, 2.408, into X for calculation, yielding a Y value of 1.811. This figure represents the predicted audience satisfaction for the web drama and ranks third among the ten web dramas, as shown in Table 4.20 below.

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Table 4.20 below presents the predicted audience satisfaction levels for the ten Chinese web dramas. As shown in Table 4.20, *Go East* is predicted to have the highest audience satisfaction among the sample, followed by *Are You the One*. Among them, the Chinese web drama with the lowest predicted audience satisfaction is *The Vanished Elephant*, according to the present study's predictions.

Table 4.20

Predicted Audience Satisfaction Levels for the Ten Recent Chinese Web Dramas

Ranking	Web Drama Title	Value of VM	Value of SMCS	Group	Equation	Predicted AS
1	*Go East*	3.759	168000	High-level group	Equation 1	2.742
2	*Are You the One*	2.782	142000	High-level group	Equation 1	2.069
3	*Love Game in Eastern Fantasy*	2.408	722000	High-level group	Equation 1	1.811
4	*Fangs of Fortune*	0.564	212000	High-level group	Equation 1	0.540
5	*Snowy Night Timeless Love*	1.052	59000	Low-level group	Equation 2	0.121
6	*Kill Me Love Me*	-0.421	97000	Low-level group	Equation 2	-0.363
7	*Duel of Shadows*	-1.173	4980	Low-level group	Equation 2	-0.609
8	*Hun Yin Gong Lue* (Chinese pinyin)	-1.804	518	Low-level group	Equation 2	-0.816
9	*Twenty-One Days*	-3.573	2930	Low-level group	Equation 2	-1.397
10	*The Vanished Elephant*	-3.593	747	Low-level group	Equation 2	-1.404

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4.8.3 Test of the Predicted Results of Recent Ten Chinese Web Dramas

To validate the predicted results presented in Table 4.20, this study conducted a sentiment analysis using GooSeeker software based on 438,537 comments collected from Weibo, Douban, Zhihu, and Xiaohongshu. By measuring sentiment orientation, the study efficiently obtained attribute-level audience satisfaction scores for the ten Chinese web dramas. After logarithmic transformation, data normalization, and PLS-SEM algorithm, the final values of the audience satisfaction variable were derived for the ten web dramas. Table 4.21 presents these values along with the corresponding rankings.

Table 4.21

Audience Satisfaction Ranking for Recent Ten Chinese Web Dramas

Ranking	Web Drama Title	Value of AS
1	*Go East*	4.659
2	*Are You the One*	3.655
3	*Love Game in Eastern Fantasy*	3.183
4	*Fangs of Fortune*	0.883
5	*Snowy Night Timeless Love*	0.725
6	*Kill Me Love Me*	-0.007
7	*Duel of Shadows*	-2.168
8	*Hun Yin Gong Lue* (Chinese pinyin)	-2.920
9	*Twenty-One Days*	-3.733
10	*The Vanished Elephant*	-4.277

Through this test, the researchers found that the ranking in Table 4.20 is consistent with that in Table 4.21, indicating that the two predictive equations developed in this chapter can effectively and conveniently forecast audience satisfaction for Chinese web dramas using a big data analytics approach. More importantly, this consistency

validates the practical validity, feasibility, and operability of the audience satisfaction prediction model proposed in this study. Furthermore, it highlights the significant advantages of the big data analytics approach in predictive analysis.

4.9 Chapter Summary

This chapter presents the data analysis and findings in a sequential manner. Specifically, it consists of nine sections. The first section provides an introduction to the chapter. Following this, the second section describes data cleaning and preparation procedures using SPSS 29.0. Subsequently, the third section presents preliminary analysis of the sample data, ensuring the appropriateness of multivariate techniques for the current study.

Meanwhile, using SPSS 29.0, the fourth section conducted descriptive analysis. Furthermore, to assess the reflective measurement model, the fifth section performed CCA using SmartPLS 4.1 to evaluate indicator reliability, internal consistency reliability, convergent validity, and discriminant validity. After confirming that the reflective measurement model was valid, the sixth section tested the eleven hypotheses using SmartPLS 4.1, including six direct, three mediating, and two moderating relationships. All hypotheses were supported.

Subsequently, building on the acceptance of all hypotheses, the seventh section systematically addresses the achievement of each research question and objective of

this study. Following this, the eighth section presents the application of the predictive model developed in this study, demonstrating its validity, feasibility, and practical operability. Finally, the ninth section provides a summary of the chapter.

To sum up, the empirical analyses and findings of this study reveal that web drama audience satisfaction is influenced by web drama viewing motivation, web drama exposure, audience social media engagement, and social media community size. In addition, there are direct positive associations among web drama viewing motivation, web drama exposure, and audience social media engagement. Furthermore, the findings indicate that web drama exposure and audience social media engagement mediate the relationship between viewing motivation and audience satisfaction.

Moreover, social media community size significantly moderates the relationship between viewing motivation and audience satisfaction, as well as the relationship between web drama exposure and audience social media engagement. The conclusions regarding these direct, mediating, and moderating relationships, the development of the predictive model, and the contributions of this study will be discussed in detail in the following chapter.

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CHAPTER FIVE

DISCUSSION AND CONCLUSIONS

5.1 Introduction

As a burgeoning sector of the media industry, Chinese web drama has experienced remarkable growth. In recent years, numerous popular Chinese web dramas have drawn large audiences and achieved high levels of audience satisfaction. However, certain Chinese web dramas exhibit low levels of audience satisfaction and have not achieved favorable reception among viewers. This issue may result in a decline in audience retention and negatively affect the sustainable development of the web drama industry. Critically, compounding this challenge is that Chinese web drama stakeholders have underutilized big data for audience satisfaction forecasting, which may impede their ability to conduct timely predictive analysis of web drama audience satisfaction. It amplified operational uncertainties, potentially escalating market risks.

Therefore, this study aims to develop a comprehensive predictive model of audience satisfaction in Chinese web dramas through a big data analytics approach, grounded in the theoretical frameworks of UGT and CCT. Grounded in big data analytics, the developed model enables Chinese web drama stakeholders to proactively conduct data-informed predictive analysis of audience satisfaction, thereby facilitating evidence-based targeted interventions designed to elevate audience satisfaction.

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These capabilities are projected to optimize organizational decision-making, reduce operational uncertainties, and attenuate market risks for these stakeholders.

Through big data analytics, this study demonstrates that significant and positive direct, mediating, and moderating relationships exist among the five constructs of web drama audience satisfaction, web drama viewing motivation, web drama exposure, audience social media engagement, and social media community size in the context of Chinese web dramas. As a consequence, this chapter provides a comprehensive and in-depth summary of these relationships and ultimately proposes an inclusive predictive model of audience satisfaction in Chinese web dramas.

This chapter consists of seven sections. The first section begins with an introduction, and the second section presents a discussion of the direct, mediating, and moderating relationships grounded in the empirical evidence derived from the study findings. The third section then introduces the comprehensive and validated predictive model of audience satisfaction in Chinese web dramas. The fourth section summarizes the contributions from theoretical, methodological, practical, and knowledge perspectives. The fifth section outlines the limitations of the current study. The sixth section provides concrete recommendations for future research. Finally, the seventh section concludes the chapter with a summary of the entire investigation.

5.2 Discussion of the Research Findings

To address the research questions and objectives of this study, eleven hypotheses were formulated and empirically tested, yielding findings on the direct, mediating, and moderating relationships. This section synthesizes these results through a comprehensive discussion to establish a validated predictive model of audience satisfaction in Chinese web dramas.

5.2.1 Discussion of Direct Relationships

To address the first research question and objective, this study proposes six direct hypothesized relationships among web drama audience satisfaction, web drama viewing motivation, web drama exposure, and audience social media engagement, grounded in UGT, CCT, and relevant literature. Using PLS-SEM, the significance of path coefficients was assessed to test these relationships. The evaluation results fully support all six direct hypotheses (H1 – H6). A detailed discussion of these direct relationships follows.

5.2.1.1 Relationship between Web Drama Viewing Motivation and web drama audience satisfaction

The research finding confirms Hypothesis 1, demonstrating a direct and significant positive relationship between web drama viewing motivation and web drama audience satisfaction, as evidenced by the result presented in Chapter Four. Specifically, the result indicates that higher levels of web drama viewing motivation

are consistently associated with greater web drama audience satisfaction. Thus, Hypothesis 1 is empirically supported. By leveraging a big data analytics approach, this study establishes viewing motivation as a reliable and robust predictor of audience satisfaction in the context of Chinese web dramas, thereby affirming its role as a key antecedent variable in constructing a comprehensive predictive model of audience satisfaction.

Based on big data analysis, this significant positive relationship can be further substantiated. As previously noted, big data analytics enables the capture and integration of real-time statistical datasets. Specifically, 16,057,255 social media comments collected from Weibo, Douban, Zhihu, and Xiaohongshu, along with 288 Douban scores, have been leveraged as the empirical basis for big data analytics directed at validating this relationship. Furthermore, sentiment analysis facilitates the transformation of these social media comments into structured datasets, thereby unlocking their analytical value for validating this relationship. Through statistical analysis, the results have identified the embedded relationship between viewing motivation and audience satisfaction within large-scale datasets specific to Chinese web dramas. Big data analytics facilitates the extraction of actionable, context-specific insights from large-scale data, particularly unstructured content.

According to Hu (2021) and Wang (2022), the primary motivations for viewing web dramas include entertainment, relaxation, escapism, passing time, information

seeking, and social interaction. Building on this foundation, the present study utilizes comments reflecting these motivational factors to train and test the convolutional neural network model employed in this research, thereby enhancing its deep learning performance in sentiment analysis. Furthermore, leveraging Python for sentiment analysis allows for the systematic identification and quantification of such comments, enabling the derivation of attribute values for subsequent statistical analysis; the result supports Hypothesis 1. This finding demonstrates that the core motivations, including entertainment, relaxation, escapism, passing time, information seeking, and social interaction, exert a positive influence on web drama audience satisfaction within the context of big data analytics.

This outcome is consistent with UGT, which underscores the pivotal role of user motivations in shaping media consumption and perceived gratification (McQuail & Deuze, 2020; Katz et al., 1974; West & Turner, 2020). Meanwhile, this research finding supports the conclusion drawn by Liu et al. (2022), who argue that audience value perception, defined as a form of viewing motivation, influences audience satisfaction regarding viewing experience within the context of behavioral big data generated by viewers.

While employing distinct research methods, this research finding converges with prior literature on the relationship between viewing motivation and audience satisfaction. Specifically, it echoes Suh et al. (2019), who concluded that audience

viewing motivations positively influence social viewing satisfaction. It also corroborates Tefertiller and Sheehan (2019), whose work established that TV viewing motivators reliably predict audience satisfaction. Additionally, this finding resonates with Kang and Cho (2020), who noted that viewing motivators affect audience satisfaction in differential ways.

Furthermore, it converges with Pappas et al. (2020), who demonstrated that user motivation plays a key role in determining satisfaction on social networking sites and can explain and predict such satisfaction. The shared insight between Pappas et al. (2020) and the present study provides robust evidence that viewing motivation effectively predicts audience satisfaction. This finding also echoes Periaiya and Nandukrishna (2023), who argued that viewing motivations positively and directly impact media satisfaction on over-the-top video streaming platforms. Moreover, it resonates with Jin et al. (2023), who found that motivations positively influence Malaysian university students' satisfaction regarding Instagram usage.

In summary, as a significant antecedent of audience satisfaction, web drama viewing motivation possesses substantial value for investigation and application. In response to the research problems of this study, this finding provides valuable insights for stakeholders in the Chinese web drama industry, enabling them to conduct trend forecasting of audience satisfaction by leveraging viewing motivation as a reliable and robust predictor through big data analytics. Moreover, this finding suggests

practical strategies for stakeholders to activate audience viewing needs, thereby enhancing satisfaction.

5.2.1.2 Relationship between Web Drama Viewing Motivation and Web Drama Exposure

Hypothesis 2 is supported by the research finding of a direct association between web drama viewing motivation and web drama exposure. The results presented in Chapter Four indicate that web drama exposure is significantly and positively influenced by viewing motivation. Specifically, big data analytics reveal that higher levels of viewing motivation are consistently associated with greater exposure to web dramas. Thus, Hypothesis 2 is confirmed.

Drawing on big data analysis, the robustness of this significant positive relationship can be further corroborated. Specifically, 16,057,255 social media comments sourced from Weibo, Douban, Zhihu, and Xiaohongshu and 1,728 structured data points extracted from social media metrics, leading search engines, and specialized big data platforms have been utilized as the empirical foundation for big data analytics tailored to validating this relationship. Concurrently, sentiment analysis enables the precise identification and quantification of social media comments articulating intentions related to entertainment, relaxation, escapism, passing time, information seeking, or social interaction, thereby unlocking their analytical utility for substantiating this relationship. Grounded in big data analytics, the findings have

uncovered the latent association between web drama viewing motivation and web drama exposure, while also facilitating the development of a robust predictive model derived from large-scale data.

Previous studies have identified core motivations for web drama viewing, including entertainment, relaxation, escapism, passing time, information seeking, and social interaction (Hu, 2021; Wang, 2022). Grounded in these empirical insights, the findings of the present study is in line with the core proposition of UGT, which posits that audience media consumption behaviors are strategically driven by pre-existing individual needs and motivations (Katz et al., 1974; McQuail & Deuze, 2020; West & Turner, 2020). This research finding supports the similar explanation provided by Chan-Olmsted and Wang (2022) that listening behaviors are influenced by motivations among podcast audiences in the context of large-scale data.

Although adopting distinct research methodologies, the present finding resonates with prior scholarship on the relationship between viewing motivations and media exposure. Specifically, it echoes Lin et al.'s (2018) assertion that audience motivations exert a positive influence on media exposure. Moreover, the finding resonates with Tefertiller and Sheehan's (2019) explanation that viewing motivations are positively associated with TV viewing. This behavior is widely conceptualized as a form of media exposure.

Furthermore, the finding converges with Kim and Kim's (2020a) demonstration that viewing motivations for travel reality variety programs positively predict presence. Given that presence is framed as a core dimension of viewing experience, which is partially analogous to web drama exposure, it follows that media exposure is shaped by underlying viewing motivations. In addition, the finding converges with Castro et al.'s (2021) statement that binge-watching behaviors are driven by viewer motivations. Moreover, it resonates with Ort et al.'s (2021) argument that motivations for high-dose TV drama consumption positively predict problematic media use. Additionally, the finding corroborates Zheng et al.'s (2023) analysis that motivations exert a significant influence on audience engagement in live-streaming contexts.

As a form of audio-visual content consumption, web drama exposure is often used by audiences to engage with specific web drama content (Mi et al., 2022). Like other audio-visual programs, web dramas typically need to possess strong appeal to attract large audiences in order to achieve widespread popularity (Hu, 2021). Consequently, media stakeholders are increasingly prioritizing strategies to enhance audience exposure to Chinese web dramas. The finding of this study offers a significant insight: fostering audience desire for web dramas can effectively promote viewing behavior. Furthermore, web drama viewing motivation can serve as a valuable indicator for communication researchers to predict patterns of web drama consumption.

5.2.1.3 Relationship between Web Drama Exposure and web drama audience satisfaction

In response to Hypothesis 3, this research confirms it through the empirical finding of a direct relationship between web drama exposure and web drama audience satisfaction. Specifically, the results from Chapter Four indicate that web drama exposure exerts a significant and positive influence on web drama audience satisfaction. Based on this empirical evidence, the study identifies web drama exposure as an additional robust predictor of web drama audience satisfaction. These findings demonstrate that web drama exposure constitutes a key antecedent in constructing a comprehensive predictive model of audience satisfaction in Chinese web dramas.

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Drawing on insights from big data analysis, the significant positive relationship hypothesized in this study can be further empirically substantiated. To examine this relationship, big data analytics facilitated the acquisition and integration of real-time statistical datasets derived from 16,057,255 social media comments and 2,016 structured data points. Additionally, sentiment analysis techniques were employed to extract and validate the association between web drama exposure and audience satisfaction, which is embedded within these large-scale datasets. This data-driven methodological framework not only confirms the existence of a robust positive relationship between the two constructs but also reveals its dynamic nature.

This research finding is consistent with the perspective from UGT research that media exposure or engagement in specific media activities results in need gratification and associated outcomes (Bae, 2018; McQuail & Deuze, 2020; Katz et al., 1974; West & Turner, 2020). Concurrently, this research finding supports the explanation offered by Liu et al. (2022), which posits that viewing behavior on media streaming live sports events influences audience satisfaction within the context of behavioral big data generated by viewers.

Although different research methods were employed, the present finding converges with prior literature on the relationship between media exposure and audience satisfaction. Specifically, this finding echoes Haqqu et al. (2019), who argued that greater exposure to YouTube media correlates with higher audience satisfaction. Meanwhile, this research finding corroborates the assertion by Suh et al. (2019) that viewing sports broadcasts enhances audience satisfaction on sporting events. Additionally, this research discovery resonates with the inference from Kim and Kim (2020a) that audience behavior positively impacts satisfaction with travel reality variety programs.

Furthermore, it converges with the argument by Tkalac Verčič and Špoljarić (2020) that audiences achieve high satisfaction levels through rich communication channels, whereas single-channel environments lead to lower satisfaction. Finally, this finding

also corroborates the viewpoint from Iwanowska et al. (2023) that a significant positive association exists between news media exposure and life satisfaction during the COVID-19 pandemic.

Researchers can facilitate trend forecasting of audience satisfaction by leveraging web drama exposure as a reliable and robust predictor through the application of big data analytics, thereby enabling proactive and targeted interventions to enhance satisfaction. In empirical terms, audiences exhibit a consistent tendency to engage selectively with web dramas congruent with their preferences, while largely disregarding content they perceive as unappealing. To enhance audience satisfaction, stakeholders within the Chinese web drama industry should prioritize the implementation of strategies directed at augmenting both the frequency and duration of audience exposure to diverse content offerings. Such objectives may be realized through the adoption of intensified promotional campaigns, targeted advertising initiatives, and the optimization of content visibility across digital platforms.

5.2.1.4 Relationship between Web Drama Viewing Motivation and Audience Social Media Engagement

In addressing Hypothesis 4, the current study provides empirical corroboration by establishing a direct relationship between web drama viewing motivation and audience social media engagement though big data analytics, identifying the former as a significant predictor of the latter. Specifically, the hypothesis-testing results

detailed in Chapter Four demonstrate a statistically significant positive association between these two constructs: higher levels of web drama viewing motivation are associated with increased levels of audience social media engagement. Therefore, Hypothesis 4 is empirically supported.

Big data analysis strengthens the evidence for this significant positive relationship. A total of 16,057,255 social media comments from Weibo, Douban, Zhihu, and Xiaohongshu, and 1,440 structured data points from social media metrics have been utilized as the empirical foundation for big data analytics designed to validate this relationship. Sentiment analysis identifies and quantifies comments expressing motivations such as entertainment, relaxation, escapism, time passing, information seeking, or social interaction, enhancing their value for analysis. The findings confirm the link between web drama viewing motivation and audience social media engagement, thereby supporting a robust predictive model based on large-scale data. Moreover, this finding also indicates that individuals may engage with social media driven by the same motivations underlying their web drama exposure.

This finding is in line with UGT, which posits that motivations underlying the use of one medium may drive exposure to other media (Katz et al., 1974; McQuail & Deuze, 2020; West & Turner, 2020), as well as with CCT, which suggests that audiences perceive social media participation within the same content domain as a complementary form of media engagement (Jiang & Liu, 2022; Neyazi et al., 2019;

Zhang et al., 2020). Meanwhile, this research finding supports the explanation offered by Tsai and Lin (2023) that research on the motivations for social TV usage has been conducted to better understand audience behavior, particularly social media engagement behavior, based on large-scale social media data.

Despite employing divergent research approaches, this finding resonates with prior academic literature on the link between viewing motivations and audience social media engagement. Specifically, this finding corroborates Odunaiya et al. (2020): the integration of TV and social media into Social TV has significantly enhanced viewers' connectivity and content engagement through social media interactions. Social TV, characterized by multi-screening and multitasking, enables audiences to follow preferred programs, share content, transform TV viewing into online events, and interact with others during and after broadcasts. This study echoes the emergence of social TV, showing that web drama audiences are inclined to share content and engage with others during and after broadcasts.

Additionally, this finding corroborates Lin et al. (2018), who showed that social entertainment as a viewing motivation affects social TV usage. It also resonates with Kim and Kim (2020b), who found that motivations positively influence flow experience and drive the use of social live streaming for sporting events. Furthermore, it converges with Habes (2019), who argued that individual motivations directly affect general social media use and facilitate cross-platform interactions in

livestreaming contexts. The finding also corroborates Khoshaim (2020), who identified motivations for second-screen use involving simultaneous discussion of TV content on secondary devices.

Additionally, this result converges with Kim et al. (2021a), who demonstrated that social TV viewing motivations influence platform selection on social media. The findings also echo Falgoust (2022) and Oeldorf-Hirsch and Srinivasan (2021), who highlighted that perceived convenience, utility, and social interaction encourage increased social media use, as evidenced by the rising volume of comments on Chinese web dramas. Finally, this study resonates with Dong and Xie (2024), who found that short video viewing motivations shape audience engagement on Chinese TikTok.

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In recent years, there has been a growing phenomenon in which audiences, motivated by their interest in web dramas, frequently use social media to access information about these productions and engage with others to share and enhance their viewing experiences (Mi et al., 2022; Su, 2022; Wang, 2022). This study encapsulates this trend, highlighting the significant role of social media in shaping audiences' cognitive and emotional responses to web dramas. Furthermore, the finding encourages web drama stakeholders to strategically leverage social media for opinion formation, which facilitates the promotion and dissemination of Chinese web dramas, thereby enhancing their visibility, audience reach, and overall popularity.

5.2.1.5 Relationship between Web Drama Audience's Social Media Engagement and web drama audience satisfaction

In addressing Hypothesis 5, this study verifies it by demonstrating a direct relationship between audience social media engagement and web drama audience satisfaction, based on big data analytics. Specifically, the results presented in Chapter Four indicate a significant and positive association between these two variables. Higher levels of social media engagement among web drama audiences correspond to greater satisfaction on web drama. Accordingly, Hypothesis 5 receives empirical support. Employing a big data analytics framework, the present study identifies audience social media engagement as a statistically significant and robust antecedent in the development of a comprehensive predictive model for audience satisfaction in Chinese web dramas.

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Big data analysis fortifies the empirical evidence for this significant positive relationship. Specifically, a total of 16,057,255 social media comments and 1,728 structured data points were employed as the empirical basis for the big data analytics framework designed to validate this association. Additionally, sentiment analysis enhances the analytical value of these data by identifying and quantifying the volume of positive and negative comments. This research finding corroborates the link between audience social media engagement and web drama audience satisfaction,

thereby supporting the development of a robust predictive model grounded in large-scale empirical data.

This finding is consistent with perspectives from UGT research indicating that differential media exposures lead to need gratification and other outcomes (McQuail & Deuze, 2020; Katz et al., 1974; West & Turner, 2020), as well as with CCT research suggesting that audiences engage in social media interactions within the same content domain as an extension of media exposure (Jiang & Liu, 2022; Neyazi et al., 2019; Zhang et al., 2020). Moreover, this finding supports the argument advanced by Zhao et al. (2019) that customers' overall satisfaction is positively influenced by their review involvement, as evidenced by big data. It also reinforces the assertion proposed by Liu et al. (2022) that audience satisfaction on sports TV programs can be affected by viewers' social media engagement within the context of behaviorally generated big data.

Although employing distinct methodological frameworks, this finding resonate with prior scholarly literature on the association between viewing motivations and audience social media engagement. Specifically, this finding corroborates Yoo's (2011) proposition that social media engagement within a specific content domain exerts a positive effect on audience satisfaction in that domain. Concurrently, it echoes Suh et al.'s (2019) assertion that sharing social viewing experiences during

sports broadcasts by viewing and discussing events via social media positively enhances audience satisfaction on sporting events.

This finding further converges with Kim and Kim's (2020b) conclusion that flow experiences among social live streaming service users have a positive impact on their satisfaction on the service. Additionally, this research finding resonates with Majeed et al.'s (2022) argument that a positive and significant relationship exists between customer social media engagement and customer satisfaction. It also converges with the conclusions of Zhao et al. (2023), Meng et al. (2023), and Cary et al. (2024), which posit that social media utilization is positively linked to life satisfaction; namely, social media usage can contribute to increased life satisfaction.

This research finding elucidates the impact of audience social media engagement on web drama audience satisfaction, offering new insights into the factors influencing audience satisfaction in the context of Chinese web dramas. In the social media era, studies on audience satisfaction should incorporate audience social media engagement into their analytical frameworks in the context of Chinese web dramas. Furthermore, this finding encourages web drama stakeholders to effectively stimulate audience enthusiasm for social media engagement, thereby enhancing audience satisfaction in Chinese web dramas.

5.2.1.6 Relationship between Web Drama Exposure and Audience Social Media Engagement

Hypothesis 6 is supported by the research finding of a direct relationship between web drama exposure and audience social media engagement, as revealed through big data analytics. Specifically, the results of the hypothesis testing presented in Chapter Four indicate that web drama exposure has a significant and positive effect on audience social media engagement; namely, greater exposure to web dramas is associated with higher levels of social media engagement among audiences. Therefore, this study confirms Hypothesis 6.

By leveraging big data analysis, the hypothesized significant positive relationship in this study is further empirically validated. To examine this association, big data analytics facilitated the systematic collection and integration of 3,168 structured data points extracted from social media metrics, leading search engines, and specialized big data platforms. The resulting data-driven methodological framework not only confirms the robustness of the positive relationship between the two constructs but also reveals their dynamically evolving nature.

This research finding reinforces CCT scholarship by highlighting the coexistence of diverse media forms in enhancing audiences' information-acquisition behaviors (Jiang & Liu, 2022; Neyazi et al., 2019; Zhang et al., 2020). Meanwhile, this finding supports the discovery made by Tsai and Lin (2023), which reveals that exposure to

TV entertainment programs influences social media engagement based on social media big data.

Notwithstanding the use of distinct research methodologies, this finding converges with existing scholarly literature exploring the association between media exposure and audience social media engagement. Concretely, this research finding corroborates social TV scholarship focused on the prevalent phenomenon of audiences engaging in social media comments and interactions during TV program exposure within specific content domains (Elareshi et al., 2022; Habes et al., 2022). Moreover, it aligns with Lin et al.'s (2018) assertion that audiences use social media or program-linked website interactions as an extension of their viewing experience. Both this finding and Lin et al.'s (2018) study provide similar evidence that social media engagement is increasingly common among entertainment program viewers.

In addition, this finding resonates with Suh et al.'s (2019) argument that audiences access TV-related information or exchange viewing insights via social media. It further echoes industry practices like Nielsen's 2013 launch of social TV tracking, which measures Facebook and Twitter engagement with televised content, and suggests media stakeholders should prioritize entertainment program audiences' social media engagement (Nee & Barker, 2019). Furthermore, it converges with recent observations: widespread social media sharing of TV experiences (Odunaiya et al., 2020), regular primetime TV-related Twitter activity, and second-screen usage

during TV viewing (Lin et al., 2018; Nagy & Midha, 2014; Odunaiya et al., 2020). These trends are deemed partially global and generational (Nee & Barker, 2019).

This finding also corroborates García-Perdomo's (2021) claim that social media serves as a robust social video sharing platform beyond video engagement or distribution. It echoes Mourão and Brown's (2021) conclusion that media coverage boosts social media engagement, such as reading, liking, or sharing news items. Finally, this finding converges with the argument proposed by Tsai and Lin (2023) that media stakeholders can leverage social media engagement to enhance the popularity of TV entertainment programs.

In summary, relying on big data analytics, this finding indicates that web drama audiences frequently engage with social media as a complementary practice to viewing web dramas. This finding suggests that web drama stakeholders should focus on social media interactions and comments to gain timely insights into audiences' thoughts, feelings, and attitudes toward web dramas. Moreover, by analyzing the volume of social media interactions and comments, researchers can assess audience exposure to web dramas. Following an in-depth discussion of the six direct relationships, this study proceeds to examine three mediating associations.

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5.2.2 Discussion of Mediating Relationships

Addressing the second research question and objective, this study proposes three hypothesized mediating relationships. These relationships specifically target the link between web drama viewing motivation and web drama audience satisfaction. Among the three hypotheses, Hypothesis 7 assumes the mediating effect of web drama exposure; Hypothesis 8 postulates the mediating effect of audience social media engagement; and Hypothesis 9 hypothesizes the serial mediating effects of web drama exposure and audience social media engagement. After testing the three mediating hypotheses using the bootstrap confidence interval, this study finds that all hypothesized mediating effects (H7, H8, and H9) are supported by the results. The following section provides a detailed discussion of these mediating relationships.

5.2.2.1 Mediating Effect of Web Drama Exposure: Linking Web Drama Viewing Motivation to Web Drama Audience Satisfaction

The research finding regarding this mediating relationship confirms Hypothesis 7, based on big data analytics. Specifically, based on the test results for the mediating effect and the significant path coefficient from web drama viewing motivation to web drama audience satisfaction presented in Chapter Four, web drama exposure is found to partially mediate the relationship between web drama viewing motivation and web drama audience satisfaction. Therefore, Hypothesis 7 is supported.

Meanwhile, research has revealed that web drama viewing motivation exerts a positive effect on web drama exposure, which in turn positively influences web drama audience satisfaction. This indicates that web drama exposure mediates the relationship between viewing motivation and audience satisfaction, supporting the existence of a positive indirect effect of viewing motivation on satisfaction. Taken together, these findings demonstrate that both web drama viewing motivation and social media engagement are robust predictors of audience satisfaction in the context of Chinese web dramas. By leveraging big data analytics, these results further substantiate that the two variables serve as key antecedents in the development of a comprehensive predictive model of audience satisfaction.

Big data analysis strengthens the empirical evidence for this positive indirect relationship. Specifically, the big data analytics framework developed to validate this mediating relationship drew on a total of 16,057,255 social media comments and 2,016 structured data points as its empirical foundation. Using PLS-SEM, this research finding confirms the mediating relationship, thereby supporting the development of a robust predictive model based on large-scale empirical data.

This research finding is consistent with UGT research, which posits that audience demands drive differential media exposure, leading to need gratification and subsequent outcomes (McQuail & Deuze, 2020; Katz et al., 1974; West & Turner, 2020). Moreover, this research finding supports prior studies asserting that web

drama viewing motivation has a positive effect on web drama exposure (Chan-Olmsted & Wang, 2022), which in turn influences web drama audience satisfaction within the context of big data analytics (Liu et al., 2022).

While adopting distinct research methods, this finding converges with existing scholarly literature exploring the mediating role of media exposure in the relationship between motivation and satisfaction. Specifically, this research finding corroborates the investigation from Borghese et al. (2015) that claims TV viewing as a lifestyle behaviour mediates the association between bedroom TV access and adiposity among Canadian females. Additionally, it resonates with the analysis from Do Carmo et al. (2020) that highlights TV viewing time serves as a significant mediator in the relationship between perceived environmental unsafety and body mass index among school-aged children. Moreover, it converges with Goel et al. (2022) that announce impulsive online purchasing mediates the effect of impulsive online buying tendency on customer satisfaction.

In addition, this research discovery echoes the statement made by Tefertiller and Sheehan (2019) that certain motivations for TV viewing are positively associated with viewing patterns, while viewer involvement with programming has a positive impact on satisfaction. Furthermore, this finding resonates with the assertion from Kim and Kim (2020a) that presence, defined as the subjective viewing experience, mediates the relationship between viewing motivation and viewing satisfaction.

By means of a big data analytics approach, this research finding reveals that viewing motivation positively influences audience satisfaction through the mediator of web drama exposure in the context of Chinese web dramas. This mediation effect further underscores the significance of the two variables, namely web drama viewing motivation and web drama exposure, in enhancing web drama audience satisfaction. In the meantime, this mediating relationship provides web drama stakeholders with a robust pathway for predicting audience satisfaction.

5.2.2.2 Mediating Effect of Web Drama Audience's Social Media Engagement: Linking Web Drama Viewing Motivation to Web Drama Audience Satisfaction

Hypothesis 8 is supported by the finding of a mediating effect of audience social media engagement in the relationship between web drama viewing motivation and web drama audience satisfaction. Specifically, the test results of the mediating relationship, presented in Chapter Four, confirm the significance of the indirect path from web drama viewing motivation to web drama audience satisfaction. Meanwhile, a significant path coefficient was observed for the direct effect from web drama viewing motivation to web drama audience satisfaction, indicating that audience social media engagement serves as a partial mediator in this relationship. This finding suggests that the influence of viewing motivation on satisfaction is transmitted, in part, through increased engagement on social media platforms. Consequently, this study confirms Hypothesis 8.

The findings of this study support Hypothesis 8, which posits a mediating role of audience social media engagement in the relationship between web drama viewing motivation and web drama audience satisfaction. Specifically, as demonstrated in Chapter Four, the significant path coefficients from web drama viewing motivation to web drama audience satisfaction, along with the results of mediation analysis, provide empirical evidence that audience social media engagement partially mediates this relationship. Therefore, Hypothesis 8 is confirmed.

Furthermore, given that web drama viewing motivation positively influences audience social media engagement, which in turn enhances web drama audience satisfaction, this study demonstrates that viewing motivation exerts a positive indirect effect on audience satisfaction through the mediating role of social media engagement. Taken together, these findings suggest that web drama viewing motivation and audience social media engagement are reliable predictors of web drama audience satisfaction, and that both variables serve as key antecedents in the development of a comprehensive predictive model of such satisfaction.

Big data analytics consolidates the empirical evidence for this positive indirect relationship. Specifically, the big data analytics framework developed to verify this mediating relationship was grounded in a total of 16,057,255 social media comments and 1,728 structured data points as its empirical basis. By employing PLS-SEM, this

study's findings validate this mediating relationship, thereby underpinning the construction of a robust predictive model rooted in large-scale empirical data.

This research finding further strengthens the perspective derived from UGT that audience needs drive differential media use, resulting in demand gratification and subsequent outcomes (McQuail & Deuze, 2020; Katz et al., 1974; West & Turner, 2020), as well as the viewpoint from CCT that audiences engage in social media activities within the same content domain as an extension of media exposure (Jiang & Liu, 2022; Neyazi et al., 2019; Zhang et al., 2020). It highlights the integrative potential and theoretical vitality of combining UGT and CCT frameworks. Moreover, this study supports prior research indicating that web drama viewing motivation drives audience social media engagement (Tsai & Lin, 2023), which in turn influences differential satisfaction with web dramas, as evidenced by big data analytics (Zhao et al., 2023).

Despite employing distinct research methodologies, this finding converges with extant scholarly literature investigating the mediating function of audience social media engagement in the association between motivation and satisfaction. Specifically, this finding resonates with the conclusion from Lisitsa et al. (2020) that social media use can function as a mediator in the relationship between age and loneliness. Meanwhile, it echoes the argument put forward by Khatri et al. (2021)

that social media engagement mediates the association between pandemic-related reactions and employee well-being during the COVID-19 pandemic.

Furthermore, this research finding resonates with the assertion from Qalati et al. (2021) that social media adoption plays a mediating role in the effect of technological, organizational, and environmental factors on the performance of small and medium-sized enterprises. In addition, it corroborates the research from Susanto et al. (2021) that social media usage plays a mediating role in the relationship between entrepreneurial orientation and the performance of small and medium-sized enterprises. Besides, this research finding converges with the assertion from Tylka et al. (2023) that social media usage serves as a mediator in the association between motivations for social media use and body satisfaction.

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Leveraging a big data analytics approach, this finding sheds light on the mediating mechanism through which web drama viewing motivation positively influences web drama audience satisfaction via audience social media engagement. This mediating pathway further enriches the predictive model of audience satisfaction in the context of Chinese web dramas, underscoring the importance of both web drama viewing motivation and audience social media engagement as key contributors to enhanced audience satisfaction.

5.2.2.3 Sequential Mediating Effects of Web Drama Exposure and Audience Social Media Engagement: Linking Web Drama Viewing Motivation to Web Drama Audience Satisfaction

With regard to Hypothesis 9 of the current study, this research validates it through the finding of sequential mediating effects of web drama exposure and audience social media engagement in the relationship between web drama viewing motivation and web drama audience satisfaction. Specifically, the test results for this sequential mediation effect, along with the significant path coefficient from web drama viewing motivation to web drama audience satisfaction presented in Chapter Four, indicate that web drama exposure and audience social media engagement sequentially and partially mediate the association between web drama viewing motivation and web drama audience satisfaction. As a consequence, Hypothesis 9 is fully supported.

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This study reveals that web drama viewing motivation positively and indirectly influences web drama audience satisfaction through a sequential mediation pathway. Specifically, viewing motivation enhances web drama exposure, which in turn increases audience social media engagement, ultimately leading to higher levels of audience satisfaction. The findings demonstrate that web drama viewing motivation, web drama exposure, and audience social media engagement are robust predictors of audience satisfaction. These three constructs are thus identified as critical antecedents in establishing a comprehensive predictive model for audience satisfaction in Chinese web dramas.

Big data analytics offers rigorous empirical confirmation of this positive sequential mediating relationship. Specifically, the analytical framework leveraging big data to substantiate the sequential mediation mechanism is grounded in an extensive dataset comprising 16,057,255 social media comments and 3,456 structured observations. By employing PLS-SEM, this study empirically verifies the proposed sequential mediating pathway, thereby enabling the development of a robust predictive model firmly anchored in large-scale empirical evidence.

This research finding is consistent with the perspective derived from UGT that audience demands drive diverse media usage, leading to need satisfaction and subsequent outcomes (McQuail & Deuze, 2020; Katz et al., 1974; West & Turner, 2020), as well as for the stance advanced by CCT that audiences engage in social media participation within the same content domain as an extension of media exposure (Jiang & Liu, 2022; Neyazi et al., 2019; Zhang et al., 2020). Moreover, it demonstrates the significant integrative value of combining CCT and UGT frameworks. Meanwhile, this research finding supports prior studies by Liu et al. (2022) and Zhao et al. (2019), which assert that viewing motivation positively influences media exposure, and that increased media exposure in turn enhances social media engagement, ultimately contributing to higher audience satisfaction in the Internet era as evidenced by big data analytics.

Notwithstanding adopting divergent research approaches, the present finding converges with existing academic scholarship exploring the sequential mediating roles of web drama exposure and audience social media engagement in the link between web drama viewing motivation and web drama audience satisfaction. Specifically, this research finding echos the study by Borghese et al. (2015), which asserts that television viewing, conceptualized as a lifestyle behavior, mediates the association between bedroom TV access and adiposity among Canadian females. Moreover, it corroborates the findings of Do Carmo et al. (2020), who demonstrate that TV viewing duration acts as a significant mediator in the relationship between perceived environmental unsafety and body mass index among school-aged children.

In addition, it corroborates the work of Susanto et al. (2021), which provides empirical validation for the mediating role of social media usage in linking entrepreneurial orientation to the performance of small and medium-sized enterprises. Moreover, this research finding converges with the assertion from Tylka et al. (2023) indicating that social media usage serves as a mediator in the association between motivations for social media use and body satisfaction. Meanwhile, it echoes the argument put forward by Khatri et al. (2021) showing that social media engagement mediates the link between pandemic-related reactions and employee well-being during the COVID-19 pandemic.

Additionally, this study further echoes findings from social TV research conducted

by Nee and Barker (2019), Suh et al. (2019), and Odunaiya et al. (2020), which demonstrate that media exposure influences social media engagement, as audiences frequently use social media platforms to share their viewing experiences. Concurrently, the present result corroborates Lin et al. (2016), who argue that social TV participation mediates the positive effect of viewing experience on satisfaction with favorite programs. It also converges with Kim and Kim (2020a), whose work reveals that presence, defined as a viewing experience characterized by involvement, attention, and engagement in reality programming, mediates the relationship between motivation to watch travel reality variety shows and viewing satisfaction. Finally, this finding resonates with Ji (2023), who observes that Chinese web drama audiences commonly share their viewing experiences derived from underlying needs across multiple social media platforms such as Weibo and Douban.

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By leveraging a big data analytics approach, this finding successfully establishes the sequential mediating mechanism. It reveals that web drama viewing motivation positively influences web drama audience satisfaction through the sequential mediation of web drama exposure and audience social media engagement. First, this sequential mediation effect further underscores the significance of the three antecedents: web drama viewing motivation, web drama exposure, and audience social media engagement, in enhancing satisfaction among Chinese web drama audiences. In the meantime, the sequential mediating relationship extends the

predictive framework of audience satisfaction in the context of Chinese web dramas and provides stakeholders with a robust pathway for predicting audience satisfaction.

Furthermore, this finding highlights the complexity of Chinese web drama audiences' psychological and behavioral patterns, encouraging communication scholars to conduct comprehensive investigations into audience psychology and behavior in the Internet era. Ultimately, the empirical findings regarding the three mediating relationships confirm that the conceptual model proposed in this study aligns with a multi-step multiple mediation model (Hayes, 2009), specifically a serial multiple mediation model (Hayes, 2022).

5.2.3 Discussion of Moderating Relationships

This study addresses the third research question and the corresponding objective by proposing two hypothesized moderating relationships, namely H10 and H11. Hypothesis 10 posits that social media community size moderates the direct relationship between web drama viewing motivation and web drama audience satisfaction. Hypothesis 11 assumes that social media community size also moderates the association between web drama exposure and audience social media engagement. These hypotheses are grounded in UGT, CCT, and relevant literature. After completing the hypothesis testing of the two moderating relationships using SmartPLS 4.1, this study confirms that both moderating hypotheses (H10 and H11)

are supported by the examination results. The following section provides a more detailed discussion of these two moderating relationships.

5.2.3.1 Moderating Effect of Social Media Community Size: On the Direct Link between Web Drama Viewing Motivation and Web Drama Audience Satisfaction

In recent years, academic attention has increasingly focused on social media community size due to its significant influence on media use and effects (Nepomuceno et al., 2020). Drawing on prior research that identifies community size as a key contextual factor (Dolan, 2015; Jiang et al., 2019; Nepomuceno et al., 2020; Yang et al., 2016), this study formulates Hypothesis 10 by incorporating social media community size as a moderating variable. To test Hypothesis 10, the study examines the corresponding empirical results and confirms the moderating effect of social media community size in the direct relationship between web drama viewing motivation and audience satisfaction. As evidenced by the significant coefficient of the interaction term reported in Chapter Four, social media community size is shown to moderate the impact of viewing motivation on audience satisfaction. Consequently, Hypothesis 10 is supported.

Moreover, the results show that the path coefficient is positive when social media community size moderates this relationship, indicating that social media community size positively strengthens the association between web drama viewing motivation

and audience satisfaction. In addition, given the large effect size of the interaction term, the current study affirms the substantial nature of this moderating effect, highlighting the robustness of social media community size as a predictive factor. By integrating these findings, including the statistical significance of the interaction term, the positive path coefficient, and the large effect size, the study concludes that social media community size is a strong predictor of audience satisfaction in Chinese web dramas. This suggests that social media community size serves as an important antecedent for developing a comprehensive predictive model of audience satisfaction.

Big data analytics delivers rigorous empirical support for the hypothesized moderating effect. Specifically, the analytical framework leveraging big data to substantiate the moderating mechanism relies on real-time statistical datasets derived from 16,057,255 social media comments and 576 structured observations. By applying PLS-SEM, this study empirically validates the proposed moderating pathway, thereby facilitating the development of a robust predictive model grounded in large-scale empirical evidence.

This research finding is in line with the perspective from UGT that differential media exposure or engagement in alternative activities leads to demand gratification and associated outcomes (McQuail & Deuze, 2020; Katz et al., 1974; West & Turner, 2020), as well as with the stance in CCT research indicating that audiences extend

media exposure through social media engagement within the same content domain (Jiang & Liu, 2022; Neyazi et al., 2019; Zhang et al., 2020). Furthermore, this finding suggests that integrating UGT and CCT frameworks offers practical implications for communication research.

Despite differing research methodologies, this finding converges with existing scholarly literature on the positive moderating role of social media community size in the direct relationship between web drama viewing motivation and audience satisfaction. Specifically, it resonates with Yang et al. (2016), who demonstrate that online community affiliation positively moderates the link between reciprocity and satisfaction. Individuals with higher affiliation report greater satisfaction as reciprocity increases, compared to those with lower affiliation. Moreover, the finding corroborates Zhang et al. (2022), whose research shows that perceived social support strengthens the association between intrinsic community-related motivation and life satisfaction. Individuals experiencing higher levels of social support exhibit greater gains in life satisfaction as intrinsic motivation rises.

However, this result contrasts with Liu and Pan (2020), who find that the positive effect of linking social capital on life satisfaction among rural-to-urban migrants is attenuated by larger friendship network sizes. Specifically, the increase in life satisfaction diminishes as network size grows. Similarly, it diverges from Morelli et al. (2023), who report that the number of friends amplifies a negative relationship

between motivation and academic satisfaction. Students with more friends experience a sharper decline in satisfaction when motivation increases.

These discrepancies may stem from methodological differences, particularly this study's use of big data analytics. The large-scale, real-time nature of the data enhances the reliability and generalizability of the findings, lending stronger empirical support to the positive moderating effect of social media community size. They may also arise from differences in research samples. Different study participants have distinct psychological and behavioral characteristics, which may influence the moderating effect of the moderator variable.

In summary, this research finding reveals a moderation mechanism whereby social media community size positively moderates the direct association between web drama viewing motivation and audience satisfaction. As a significant antecedent of audience satisfaction, social media community size reflects the profound influence of social media on Chinese web drama audiences. Therefore, when predicting and evaluating audience satisfaction, web drama stakeholders should accurately capture the value of social media community size.

5.2.3.2 Moderating Effect of Social Media Community Size: On the Link between Web Drama Exposure and Audience Social Media Engagement

Regarding Hypothesis 11, this research validates it through the finding of a significant moderating effect of social media community size on the relationship between web drama exposure and audience social media engagement. Specifically, based on the statistically significant result for the interaction term reported in Chapter Four, the study demonstrates that social media community size moderates the association between web drama exposure and audience social media engagement. Furthermore, given the medium effect size observed for this interaction, the analysis provides additional support for the substantive nature of this moderating effect. Therefore, Hypothesis 11 is supported.

At the same time, the examination results show that the path coefficient is positive when the relationship between web drama exposure and audience social media engagement is moderated by social media community size. Therefore, it can be concluded that social media community size exerts a positive moderating effect on this relationship. Moreover, given that social media engagement positively influences web drama audience satisfaction, this finding suggests that social media community size should be included as a predictor of satisfaction among Chinese web drama audiences by moderating the link between web drama exposure and audience social media engagement. This indicates that social media community size can serve as an

additional antecedent in constructing a comprehensive predictive model of audience satisfaction in Chinese web dramas.

Big data analytics provides rigorous empirical validation for this moderating relationship. Specifically, the analytical framework that employs big data to substantiate the moderating mechanism is rooted in 3,456 structured observations. Through the application of PLS-SEM, this study empirically confirms the hypothesized moderating pathway, thereby facilitating the development of a robust predictive model firmly underpinned by large-scale empirical evidence.

This research finding further strengthens the perspective from UGT that varying levels of media exposure or participation in alternative activities lead to demand gratification and other outcomes (McQuail & Deuze, 2020; Katz et al., 1974; West & Turner, 2020), as well as the viewpoint from CCT that audiences typically engage in social media interactions with content similar to previously consumed media as an extension of their media exposure (Jiang & Liu, 2022; Neyazi et al., 2019; Zhang et al., 2020). The finding suggests that integrating UGT and CCT frameworks offers additional references and valuable insights for communication research.

Although different research methods were employed, the present finding converges with prior literature on the moderating effect of social media community size on the relationship between media exposure and social media engagement. Specifically, this

finding resonates with the conclusion drawn by Dolan (2015) that social media community size positively moderates the relationship between entertaining content and social media engagement behavior. Specifically, entertaining content in large-sized social media communities exerts a stronger influence on engagement behavior compared to that in medium-sized and small-sized communities.

Meanwhile, this result aligns with Arya et al. (2019), who argue that the presence of an online brand community positively moderates the relationship between perceived brand authenticity and consumers' brand attachment. More specifically, individuals who actively participate in a brand's online community exhibit greater increases in brand attachment as perceived authenticity rises, compared to those engaging in passive participation.

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However, this finding diverges from Nepomuceno et al. (2020), who contend that social media content is not associated with commercial performance in large online communities, but that the relationship between content and commercial performance is moderated by community size in medium-sized communities. A potential explanation for this discrepancy lies in methodological differences. Unlike the content analysis approach used by Nepomuceno et al. (2020), the current study employs big data analytics to examine the moderating effect. Given that the big data analytics approach can provide more credible and robust data samples for academic research (Babbie, 2020; Boyle & Schmierbach, 2024; Clark et al., 2022; Hair et al.,

2019b), the finding of this study is underpinned by a stronger empirical foundation and thus possess greater credibility.

Collectively, this research reveals a moderation mechanism whereby social media community size positively moderates the link between web drama exposure and audience social media engagement. It further demonstrates that social media community size is a significant antecedent of audience satisfaction. Overall, the research findings pertaining to the three mediating relationships and two moderating associations delineated above demonstrate that the conceptual model of this study constitutes a moderated multi-step multiple mediation model (Hayes, 2009); more precisely, it represents a specific form of the moderated serial multiple mediation model (Hayes, 2022).

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5.3 Predictive Model of Audience Satisfaction in Chinese Web Dramas

The aim of the present study is to develop a comprehensive predictive model of audience satisfaction in Chinese web dramas through big data analytics, informed by UGT and CCT. Guided by this aim, the study proposes four research questions and corresponding research objectives. Building on these, eleven research hypotheses are advanced based on UGT, CCT, and relevant literature. These hypotheses collectively form a moderated multi-step multiple mediation model and constitute a hypothesized predictive framework encompassing the constructs of web drama audience satisfaction, web drama viewing motivation, web drama exposure, audience social

media engagement, and social media community size.

To test these hypotheses, sample data were collected for 288 Chinese web dramas via major streaming platforms, including Tencent Video, iQIYI, Youku, Mango TV, Bilibili, and SOHU Video. Big data analytics, supported by advanced big data technologies and sentiment analysis techniques, was applied to analyze these data. Subsequently, the hypotheses were empirically examined using SPSS 29.0 and SmartPLS 4.1. All test results indicate that the proposed hypotheses are statistically supported, confirming the robustness of the theoretical model. Based on the empirical findings and a thorough discussion of the direct, mediating, and moderating relationships identified in the study, this research provides answers to the four research questions as follows:

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1. There exist six direct and positive effects in the relationships between web drama viewing motivation, web drama exposure, audience social media engagement, and web drama audience satisfaction, including web drama viewing motivation positively affects web drama audience satisfaction, web drama viewing motivation has a positive impact on web drama exposure, web drama exposure positively influences web drama audience satisfaction, web drama viewing motivation positively impacts on audience social media engagement, audience social media engagement positively affects web drama audience satisfaction, web drama exposure has a positive influence on audience social media engagement.

2. There are three mediating effects in the relationship between web drama viewing motivation and web drama audience satisfaction, including the mediating effect of web drama exposure, the mediating effect of audience social media engagement, and the sequential mediating effect of web drama exposure and audience social media engagement.
3. There exist two moderating effects of social media community size, separately, one is in the direct relationship between web drama viewing motivation and web drama audience satisfaction, the other is in the association between web drama exposure and audience's social media engagement.
4. web drama viewing motivation, web drama exposure, audience social media engagement, and social media community size are the significant antecedents to establish a predictive model of audience satisfaction in Chinese web dramas.

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Meanwhile, the four research objectives of this study were developed in direct response to the four research questions in a sequential manner, establishing clear and corresponding relationships. Consequently, all four research objectives are considered achieved, as each research question has been satisfactorily addressed. Based on the answers to these research questions, the present study has established a comprehensive predictive model of audience satisfaction in Chinese web dramas (see Figure 2.3). The development of this predictive model fulfills the aim of this study.

5.4 Research Contributions

As previously noted, certain Chinese web dramas demonstrate relatively low levels of audience satisfaction and have failed to gain favorable reception among viewers. Crucially, this issue is compounded by the underutilization of big data among Chinese web drama stakeholders for audience satisfaction forecasting. In response to these problems, this study aims to develop a comprehensive predictive model of audience satisfaction in Chinese web dramas using a big data analytics approach, grounded in the theoretical frameworks of UGT and CCT.

Through predictive modeling, this study has accomplished the research aim and filled existing gaps in knowledge, theory, methodology, and practical application, thereby making corresponding research contributions. Specifically, the research contributions of this study are systematically delineated from four distinct perspectives: knowledge, theory, methodology, and practice. These contributions facilitate the resolution of the aforementioned research problems.

5.4.1 Knowledge Contributions

First, this study introduces an original framework for the antecedents of audience satisfaction in Chinese web dramas, identifying them as web drama viewing motivation, web drama exposure, audience social media engagement, and social media community size. This finding addresses the existing research gap concerning the limited understanding of factors contributing to audience gratification in the

context of Chinese web dramas. These efforts allow scholarly research on audience satisfaction to better align with and respond to the dynamic growth of the web drama industry.

Second, this study provides novel insights into the mediating roles of web drama exposure and audience social media engagement in shaping satisfaction within the context of Chinese web dramas. Notably, it reveals a sequential mediation mechanism: exposure to web dramas enhances audience engagement on social media platforms, which in turn amplifies overall satisfaction. These insights address a notable empirical gap, that is, these mediating pathways have been insufficiently examined in prior research.

Moreover, this result suggests the emergence of a social TV phenomenon in the Chinese digital entertainment landscape, wherein audiences actively share content, comment, and interact with peers during and after viewing, transforming passive consumption into interactive participation. Such dynamics reflect a shift toward a polymedia ecology, where audio-visual content consumption is increasingly combined with social media practices, thereby enriching understandings of cross-platform audience behavior.

Additionally, big data analytics demonstrate that more popular web dramas consistently attract higher volumes of attention, discussion, and sharing on social

media, which subsequently reinforces audience satisfaction through cumulative advantage. This insight provides a novel perspective by revealing that social media may amplify the *Matthew effect* in audience satisfaction, whereby popular web dramas accumulate disproportionately high levels of audience satisfaction relative to less popular ones, ultimately contributing to an increasing polarization of audience satisfaction. These insights enable web drama stakeholders to enhance audience satisfaction through strategic use of social media.

Third, this study provides a notable contribution to identifying the moderating role of social media community size in the context of web drama audience satisfaction, addressing the research gap that this effect has been insufficiently examined in empirical studies on Chinese web dramas. The findings not only confirm that social media community size is a significant factor influencing audience satisfaction, but also demonstrate its positive moderating function in shaping such outcomes. These results provide a knowledge foundation for activating the moderating effect of social media community size to enhance audience satisfaction.

Fourth, this study employs big data analytics to validate the empirical evidence from Hu (2021) and Wang (2022), corroborating that the primary web drama viewing motivations align with their identified categories: entertainment, relaxation, escapism, time passing, information seeking, and social interaction. This study strengthens the generalizability of their findings by providing further novel, large-scale quantitative

evidence. The validated insights not only deepen the understanding of web drama viewing motivations but also provide web drama stakeholders with actionable guidance for designing strategies focused on enhancing audience motivational engagement and, consequently, improving overall satisfaction.

The knowledge contributions outlined above facilitate the resolution of the aforementioned research problems. Specifically, this study identifies four antecedents of audience satisfaction and the direct, mediating, and moderating relationships among all variables. These insights enable web drama stakeholders to enhance audience satisfaction by intervening in these antecedents in a targeted manner. For example, in response to low-satisfaction web dramas, stakeholders could design content strategies aligned with viewer preferences to activate viewing motivation, launch intensified promotional campaigns and targeted advertising to boost web drama exposure, organize interactive activities within social media communities to increase audience social media engagement, and expand community outreach to grow social media community size.

5.4.2 Theoretical Contributions

First, this study contributes novel empirical evidence on audience satisfaction within UGT research in the context of Chinese web dramas, offering potential pathways to theoretical advancement. This addresses a recognized gap in the literature, specifically the limited application of UGT to audience satisfaction in the emerging

domain of web dramas. Concretely, the findings reveal that viewing motivations such as entertainment, relaxation, escapism, time passing, information seeking, and social interaction drive exposure to web dramas and or audience engagement on social media, which subsequently lead to varying degrees of gratification and satisfaction. These findings align with the core assumptions of UGT and extend the theory's applicability by providing robust insights into dynamic and interactive media consumption.

Moreover, by leveraging large-scale quantitative data, this study enhances the robustness and generalizability of UGT, providing empirically grounded support for its applicability in digital media contexts. Furthermore, this study introduces big data analytics, including advanced data mining techniques and sentiment analysis, as an innovative methodological framework in UGT research, thereby advancing the theory's methodological toolkit and enabling new avenues for scholarly inquiry.

Second, this study advances CCT research by integrating the cross-platform complementarity between video platforms and social media, thereby addressing a significant gap in how CCT accounts for dynamic, multi-platform new media ecosystems. Specifically, the findings reveal that audience social media engagement serves as a complement to web drama exposure. That is, audiences who access web drama content via video platforms frequently turn to social media to share related

content and interact with peers within the context of a given web drama. These findings are consistent with the core assumptions of CCT.

Drawing on these insights, this study enhances the robustness and generalizability of CCT by providing data-driven empirical evidence regarding the complementary roles of diverse new media platforms. Furthermore, big data analytics grounds the theoretical framework of CCT in valid and large-scale quantitative data derived from diverse patterns of new media usage, thereby more accurately reflecting the evolving media landscape of the digital age.

Third, this study makes a significant contribution to the theoretical integration of UGT and CCT in the context of predictive modeling, thereby expanding the existing knowledge base and enhancing the practical utility of both theories within a unified framework. It addresses a notable research gap: the lack of predictive models that systematically explain the integration of UGT and CCT. Specifically, the study elucidates how these two theories can be effectively combined and empirically validates their compatibility and complementarity in a predictive context through big data analytics, providing robust support for their theoretical integration. Furthermore, by integrating UGT and CCT, the model enables the coherent incorporation of all study variables and clarifies their interrelationships with other constructs, thus facilitating a more comprehensive and theoretically grounded analysis of audience satisfaction. In essence, these theoretical contributions outlined above provide a

robust foundation for the predictive modeling of audience satisfaction in Chinese web dramas, thus advancing the addressing of the aforementioned research problems.

5.4.3 Methodological Contributions

This study employs the big data analytics approach, an emerging and evolving research method (Babbie, 2020; Boyle & Schmierbach, 2024; Scharrer & Ramasubramanian, 2021). The use of this approach addresses a notable research gap: the limited availability of communication research methods capable of efficiently collecting credible, large-scale data without interfering with the subjects under investigation in the Internet era. Meanwhile, the present study develops the procedure for the big data analytics approach, which has not yet been established due to its novelty (Babbie, 2020; Boyle & Schmierbach, 2024; Croucher & Cronn-Mills, 2024). In addition, this study employed big data crawling, stratified sampling, and systematic sampling to ensure that the conclusions are generalizable to the target population. This fills a significant research gap: most quantitative new media audience studies yield non-generalizable findings due to sampling limitations.

Systematically, this study identifies six contributions of the big data analytics approach: strong predictive ability, mitigation of the *Hawthorne effect*, efficient large-scale data collection, enhanced data credibility, high population generalizability of conclusions, and significant expansion of the research scope. The

subsequent discussion provides a comprehensive and in-depth elucidation of these contributions.

First, this study achieves methodological innovation by leveraging the big data analytics approach to unlock robust predictive capabilities of the proposed model. As Mayer-Schönberger and Cukier (2013) assert, prediction lies at the core of big data. In recent years, numerous communication scholars have adopted the big data analytics approach for predictive purposes (Chaudhary et al., 2021; Liu et al., 2022; Simon & Schroeder, 2020; Woo & Mishra, 2020). Moreover, this study employs the big data analytics approach to predict audience satisfaction in recent Chinese web dramas, thereby demonstrating strong predictive power of the developed model. Accordingly, relying on the big data analytics approach, web drama stakeholders can proactively conduct data-driven predictive analyses, thus potentially improving organizational decision-making, reducing operational uncertainties and mitigating market risks.

Second, this study presents a distinctive methodological contribution by utilizing the big data analytics approach to address the long-standing *Hawthorne effect* limitation in audience research through a robust non-intrusive data collection mechanism. The big data analytics approach facilitates the unobtrusive observation and analysis of social behaviors without altering the naturalistic responses of research subjects (Boyle & Schmierbach, 2024; James & Vo, 2022). In this study, the big data

analytics approach did not interfere with any Chinese web drama audience members, whose thoughts and behaviors remained authentic due to the absence of awareness of being observed. As a result, the sample data obtained are more representative of real-world conditions.

Leveraging these valid sample data, all statistical analyses, including tests of underlying statistical assumptions, assessment of the measurement model, evaluation of the structural model, and examinations of mediating and moderating effects, yielded results that support all research hypotheses. Consequently, the findings and conclusions derived from this study are more accurate and persuasive. As such, this empirical investigation employing the big data analytics approach reinforces the claim by Castellani and Rajaram (2021) that veracity constitutes a defining characteristic of big data.

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Third, relying on the big data analytics approach, this study innovatively enables the efficient collection and processing of large-scale datasets. In the present study, big data technology was employed to collect 16,057,255 pieces of unstructured data from major Chinese social media platforms. Additionally, 3,744 pieces of structured data were derived from large-scale social media comments, social media metrics, major search engines, and professional big data platforms. Next, sentiment analysis was performed on these unstructured data entries, yielding 2,304 additional structured

data points. In total, this study generated 6,048 structured data points suitable for direct use in statistical analysis.

As a consequence, the big data analytics approach confers unparalleled advantages in large-scale data acquisition. The efficient procurement of large-scale data underscores the inherent high-volume and high-velocity characteristics of big data (Castellani & Rajaram, 2021; De Mauro et al., 2015). This empirical investigation into the big data analytics approach demonstrates that the big data analytics approach furnishes extraordinarily extensive data sources, as asserted by Clark et al. (2022). It also indicates that the burgeoning prevalence of the big data analytics approach is driven by the vast repositories of publicly accessible data derived from social media and other heterogeneous sources, as contended by Boyle and Schmierbach (2024).

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Fourth, this study delivers a novel methodological advance by leveraging the big data analytics approach to generate data with enhanced credibility. As previously noted, this study collected a total of 16,057,255 unstructured data items and 3,744 structured data points from diverse digital sources. All data generated in this study authentically capture the psychological tendencies and behavioral patterns of Chinese web drama audiences. The acquired data exhibit consistency or high similarity across inter-rater assessments (different researchers) and intra-rater repeated measurements (same researcher). In sum, the acquisition of highly credible data demonstrates the veracity characteristic inherent to big data (Castellani & Rajaram, 2021).

Fifth, this study makes a novel methodological contribution by leveraging the big data analytics approach to enhance the generalizability of conclusions on audience satisfaction in Chinese web dramas to the target population (Babbie, 2020; Boyle & Schmierbach, 2024; Scharrer & Ramasubramanian, 2021). Specifically, the big data analytics approach furnishes extraordinarily extensive data sources, which in turn underpin the strong generalizability of this study's conclusions. Moreover, the big data analytics approach supports the use of probability sampling in this study, where a sample of 288 Chinese web dramas was selected from major streaming platforms to ensure the sample's representativeness. Furthermore, the successful application of the predictive model to ten recent Chinese web dramas in Chapter Four demonstrates that this model, developed through the big data analytics approach, is applicable to the target population.

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The high population generalizability of conclusions achieved through the big data analytics approach underscores the notable characteristics of big data, specifically high volume and veracity (Castellani & Rajaram, 2021; De Mauro et al., 2015). The big data analytics approach transcends the logic of traditional audience research in the empirical context, which relies on inferring population characteristics through non-probability sampling, thereby contributing to the advancement of communication research.

Sixth, this study contributes a novel methodological advancement by applying big data analytics to significantly expand the scope of research. Temporally, the study focuses on Chinese web dramas premiered from 2018 to the present, as of August 15, 2024. In terms of platform coverage, it includes all Chinese web dramas with accessible big data from six major streaming platforms: Tencent Video, iQIYI, Youku, Mango TV, Bilibili, and SOHU Video. From a data perspective, the study draws on real-time statistical datasets collected from large-scale social media comments, social media engagement metrics, major search engines, and professional big data analytics platforms. With regard to research subjects, this study investigates audience satisfaction and its antecedents in the context of Chinese web dramas. The significant expansion of the research scope reflects the characteristic of variety in big data (Castellani & Rajaram, 2021). As emphasized by Castellani and Rajaram (2021) and Hair et al. (2019), big data has revolutionized the types and scope of research previously considered unfeasible.

In summary, this study provides novel insights into the big data analytics approach for predictive modeling of audience satisfaction in Chinese web dramas, specifically highlighting strong predictive ability, mitigation of the *Hawthorne effect*, efficient large-scale data collection, enhanced data credibility, high population generalizability of conclusions, and significant expansion of the research scope. These insights provide a methodological foundation for systematically identifying the antecedents of audience satisfaction and offer robust capacity for data-driven

predictive analyses of audience satisfaction, thereby facilitating the resolution of the aforementioned research problems.

5.4.4 Practical Contributions

First, the predictive model and equation proposed in this study make a notable contribution to the practical deployment of predictive analytics in the Chinese web drama industry by enabling real-time forecasting of audience satisfaction. This addresses the critical gap of limited empirical research to support data-driven, predictive modeling of audience satisfaction in Chinese web dramas. Specifically, this study delivers actionable, context-tailored predictive guidance for Chinese web drama stakeholders. By empirically testing and validating a predictive framework designed for the unique characteristics of the Chinese web drama industry, it provides stakeholders with step-by-step practical recommendations, including clear procedures for model formulation, data collection, and result interpretation.

Moreover, this study enables proactive decision-making to reduce operational uncertainty. Prior research has shown that the lack of actionable insights often forces stakeholders to rely on reactive, post-hoc adjustments (Adewusi et al., 2024; Adenyi et al., 2024; Shao, 2024). This study's predictive framework allows stakeholders to transition toward proactive strategies by forecasting audience satisfaction trends in advance. Furthermore, this study contributes to mitigating market risks and enhancing industry sustainability. The practical application of the predictive model

directly addresses market vulnerabilities caused by the absence of reliable forecasting tools. By accurately predicting audience satisfaction, stakeholders can potentially avoid costly misinvestments, mitigate reputational risks, and strengthen competitive resilience through alignment with evolving viewer preferences. This outcome may ultimately support the sustainable development of the Chinese web drama industry. Collectively, the data-driven predictive modeling presented in this study offers context-specific tools and strategic guidance that empower Chinese web drama stakeholders to thrive in a highly competitive and rapidly evolving media environment.

Second, this study advances the practical utility of audience satisfaction research in supporting evidence-informed policy development and the gradual improvement of regulatory frameworks in the Chinese web drama industry, thereby contributing to its long-term and sustainable growth. It addresses a significant research gap: existing literature on audience satisfaction in Chinese web dramas remains insufficient to support evidence-informed policy decision-making by governmental agencies.

The present study holds the potential to inform targeted policy and regulatory adjustments that enhance the efficacy of market oversight, foster high-quality content production and dissemination, and contribute to the sustainable long-term development of the Chinese web drama sector. Such evidence-informed policy refinements may contribute to elevating audience satisfaction in Chinese web dramas.

Concurrently, this research can support relevant governmental bodies in leveraging big data analytics to enable evidence-based policy formulation, thereby facilitating the incremental optimization of regulatory frameworks within the Chinese web drama ecosystem.

Third, this study advances understanding of web drama genres classified by audience satisfaction, providing insights for industry stakeholders. Leveraging big data analytics, the research empirically verifies that costume dramas, romantic dramas, and martial arts dramas emerge as the most audience-favored categories, providing actionable insights for content positioning and resource allocation. Furthermore, the study reveals a notable risk dimension: suspense dramas exhibit a higher propensity to elicit audience dissatisfaction, thereby presenting heightened challenges and uncertainties for industry stakeholders. These findings not only enrich the empirical understanding of audience preferences in the web drama ecosystem but also offer evidence-based guidance for stakeholders to optimize genre selection and risk mitigation strategies.

5.5 Limitations of the Present Research

Following a review of the entire thesis, this study identifies three aspects of limitations, including variable limitations, generalizability limitations, and methodological limitations. The following section provides a detailed explanation.

5.5.1 Variable Limitations

Above all, the present investigation is limited to analyzing the relationships among web drama audience satisfaction, web drama viewing motivation, web drama exposure, audience social media engagement, and social media community size. However, additional variables that could influence these relationships are not examined. For instance, exposure to newspapers and TV may affect the associations between the relevant constructs and could serve as additional antecedents in developing the predictive model of audience satisfaction in Chinese web dramas.

Moreover, the lack of comprehensive research on the moderating effect of social media community size may compromise the accuracy of the predictive model. Due to limitations in the existing literature reviewed in this study, only two hypotheses regarding this moderating effect are proposed. This restricts a more comprehensive examination of how social media community size moderates other relationships within the predictive model. In addition, with respect to the explanatory power of the structural model, web drama exposure (R^2 = 0.261) exhibits relatively weak explanatory capability, which represents a limitation of the study.

5.5.2 Generalizability Limitations

First of all, the population in this study comprises all Chinese web dramas. However, the target population includes only those Chinese web dramas with accessible big data from Tencent Video, iQIYI, Youku, Mango TV, Bilibili, and SOHU Video.

Consequently, Chinese web dramas without available big data are excluded from this study. Specifically, due to limited audience engagement for certain Chinese web dramas, real-time statistical datasets derived from large-scale social media comments, social media metrics, major search engines, and professional big data platforms cannot be obtained. This limitation prevents the application of the big data analytics approach for these cases.

In addition, due to limitations in sentiment analysis capabilities, this study did not collect the corresponding comments from Chinese web drama audiences on major social media platforms outside China, such as Twitter, Facebook, YouTube, and Instagram. The absence of big data in this domain may have a certain negative impact on the research findings and conclusions. This limitation could hinder the generalizability of the research conclusions beyond the Chinese context.

5.5.3 Methodological Limitations

Although the big data analytics approach has many advantages, it inevitably has certain limitations. First, the approach may not be applicable to all fields of communication research. Due to the lack of relevant literature and technological constraints, some research topics such as program commitment (Gong & Huang, 2022) and media loyalty (Huang et al., 2023) are difficult to investigate using big data analytics. As communication research evolves and the big data analytics approach advances, this limitation may be mitigated in the future.

Additionally, the big data analytics approach requires researchers to invest substantial time and effort in data collection. Given the massive and diverse nature of the data, investigators must dedicate significant resources to gathering big data. When necessary, additional computational equipment is required to ensure robust data crawling capabilities. At the same time, during the data crawling process, researchers must proactively prevent and address interruptions caused by software failures, network issues, or other technical challenges.

In addition, investigations employing the big data analytics approach may encounter greater challenges due to outliers. Owing to the characteristics of high volume and variety inherent in big data (Babbie, 2020; Clark et al., 2022; Castellani & Rajaram, 2021; Hair et al., 2019b), data obtained through the big data analytics approach often lack an upper bound in empirical studies, making outlier occurrences more likely. To ensure analytical accuracy, substantial time and effort must be devoted to identifying and addressing outliers in the dataset (Ridzuan & Zainon, 2022).

Meanwhile, the raw scores of the constructs are not available due to the necessary application of logarithmic transformation and data normalization within the big data analytics framework. As previously stated, these preprocessing steps are essential to ensure computational compatibility and model robustness in this study. However, they render the original data of the constructs unavailable for presentation and limit

the ability to directly interpret untransformed values. At the same time, due to the complexity of these preprocessing steps, they hinder the widespread adoption and application of the big data analytics approach in research.

Moreover, the big data collected through web crawling may contain fabricated information resulting from coordinated inauthentic behavior by Internet troll groups, which could compromise the accuracy of the research outcomes. The Chinese public security authorities have launched a series of stringent enforcement actions against such activities (Xiao, 2024; Yin, 2023). Meanwhile, major Internet companies providing social media services, such as Baidu Inc. (2024) and Tencent Inc. (2024), are actively engaged in detecting and mitigating fake data generated by both human-driven and bot-driven manipulation. Nevertheless, complete identification and elimination of such data remain extremely challenging due to the high volume and variety inherent in big data.

Furthermore, challenges remain in processing big data through sentiment analysis. As a computational method for analyzing human sentiments, opinions, and attitudes, sentiment analysis is still in the exploratory and developmental stage and faces numerous technical difficulties (Liu, 2020). It may misidentify individuals' sentiments, opinions, and attitudes, thereby introducing potential inaccuracies into the results of the big data analytics approach (Xu et al., 2022b). For instance, handling irony remains a critical challenge: although satirical comments are intended

to express negative emotions, sentiment analysis systems often misclassify their sentiment orientation (Wankhade et al., 2022). To date, sentiment analysis continues to represent an unresolved challenge in natural language processing (Abkenar et al., 2021).

5.6 Recommendations for Future Research

Following a discussion of the contributions and limitations, this study offers recommendations for future communication research, encompassing variable recommendations, generalizability recommendations, methodological recommendations, and apply recommendations. These are detailed below.

5.6.1 Variable Recommendations

Future studies may advance the field via two targeted extensions. First, researchers could integrate AI-human interaction as a mediating variable into the audience satisfaction prediction model. By examining its mediating effect, researchers could verify whether AI-human interaction serves as a robust predictor of audience satisfaction, which may enrich the novel predictive framework.

Second, researchers could extend the dependent variable to continuance exposure intention, thereby developing a new predictive model based on this outcome. Future studies may incorporate web drama exposure, audience social media engagement, web drama audience satisfaction, and social media community size as antecedent

variables, examining their influence on continuance exposure intention. This recommendation may offer valuable insights for the development of user retention strategies.

5.6.2 Generalizability Recommendations

Future research may prioritize two directions. Firstly, research on cross-border audience satisfaction in Chinese web dramas could be extended to major international social media platforms such as Twitter, Facebook, YouTube, and Instagram to enhance sample diversity across cultural contexts and strengthen the external validity of empirical findings. Such an extension could address the potential cultural bias in existing studies centered on Chinese-language platforms. Secondly, leveraging big data analytics, scholars could develop predictive frameworks for audience satisfaction with Chinese short-form videos, which constitutes a nascent sub-sector of the global digital media ecosystem.

5.6.3 Methodological Recommendations

First of all, scholars may explore optimizing the implementation workflow of big data analytics by focusing on simplifying technical thresholds and standardizing operational protocols, in an effort to reduce its operational complexity. This refinement is expected to lower barriers to entry for researchers with limited computational expertise, thereby facilitating its broader adoption in communication studies and enhancing its visibility within the academic community.

Moreover, future communication research leveraging big data analytics should prioritize collaborative interdisciplinary efforts with computer science researchers to develop systematic frameworks for detecting and mitigating large-scale inauthentic content generated by coordinated inauthentic accounts on social media platforms. Additionally, researchers are encouraged to design user-friendly, domain-specific sentiment analysis tools tailored to the constructs examined in this study, thereby advancing the application of sentiment analysis in communication research.

5.6.4 Apply Recommendations

Firstly, Future studies are recommended to employ the recurrent neural networks (RNN) as an alternative predictive modeling technique for sentiment analysis tasks (Das et al., 2023; Mienye et al., 2024; Tan et al., 2023) in communication research. According to Mienye et al. (2024), the application of RNN in NLP has supported the advancement of sentiment analysis by enabling feasible model training and inference efficiency, as well as achieving acceptable predictive accuracy. Leveraging RNN could enable future research to expand the practical implications of the current work.

Secondly, The predictive equation derived from this study is intended for operational forecasting. From the perspective of the predictive equation, audience satisfaction forecasting relies on social media platforms. However, these platforms may withdraw from the market in the future due to factors such as insufficient

competitiveness. Therefore, future forecasting efforts need to incorporate more Chinese social media platforms into the application framework to ensure the smooth implementation of predictive applications.

5.7 Summary of the Study

As a burgeoning sector of the media industry, Chinese web dramas have experienced remarkable growth. However, certain productions exhibit low levels of audience satisfaction and fail to secure positive viewer reception. This issue may precipitate reduced audience retention and adversely impact the sustainable development of the industry. Critically, exacerbating this challenge is the underutilization of big data by Chinese web drama stakeholders for audience satisfaction forecasting, which may hinder their capacity to perform timely predictive analysis. Such underutilization is amplifying operational uncertainties and potentially escalating market risks for these stakeholders.

To addressing these problems, this study aims to develop a comprehensive predictive model of audience satisfaction in Chinese web dramas using a big data analytics approach informed by UGT and CCT. Building on UGT, CCT, and related literature, this research hypothesizes the relationships among web drama audience satisfaction, web drama viewing motivation, web drama exposure, audience social media engagement, and social media community size, proposing a moderated multi-step

multiple mediation model and a hypothesized predictive framework incorporating these constructs.

Subsequently, the study systematically and efficiently collected sample data from 288 Chinese web dramas using a big data analytics approach. Specifically, 16,057,255 unstructured data entries were retrieved from leading Chinese social media platforms, including Weibo, Douban, Zhihu, and Xiaohongshu, while 3,744 structured data records were obtained directly from prominent Chinese digital sources, such as Baidu, 360 Search, Maoyan, Douban, Douyin, Kuaishou, WeChat, and Weibo. Furthermore, sentiment analysis was employed to convert unstructured social media comments into structured datasets, thereby activating their analytical utility for empirically validating the hypothesized relationships.

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Using this sample data, the study tested the eleven proposed hypotheses through PLS-SEM with the support of SPSS 29.0 and SmartPLS 4.1. Following a series of analyses, the research findings provide empirical support for all hypotheses, revealing six direct positive effects, three mediating effects, and two moderating effects among the five constructs examined. Specifically, in the context of Chinese web dramas, the findings confirm six positive direct relationships: between viewing motivation and audience satisfaction, viewing motivation and web drama exposure, web drama exposure and audience satisfaction, viewing motivation and social media engagement, social media engagement and audience satisfaction, and web drama

exposure and social media engagement. Additionally, web drama exposure and social media engagement partially mediate the relationship between viewing motivation and audience satisfaction; social media community size positively moderates the direct relationship between viewing motivation and audience satisfaction and the relationship between web drama exposure and social media engagement, respectively.

Accordingly, this study establishes an inclusive predictive model of audience satisfaction in Chinese web dramas based on a big data analytics approach. Subsequently, by applying this predictive model, the study confirms its validity, practicality, and operational feasibility in prediction, demonstrating the robust predictive capability of big data analytics. Upon completion of the application, the study identified the finalized predictive model, thereby achieving the research aim.

Based on big data analytics, the developed model empowers Chinese web drama stakeholders to proactively carry out data-driven predictive analysis of audience satisfaction, thereby enabling evidence-based targeted interventions directed toward enhancing audience satisfaction. These capabilities are projected to optimize organizational decision-making, reduce operational uncertainties, and mitigate market risks for these stakeholders. In this way, it contributes to addressing the research problems identified in the present study. Moreover, this study makes several contributions: it advances knowledge regarding the constructs of this study, enriches

and extends UGT and CCT, applies emerging research methods, and provides actionable insights for governmental agencies and web drama stakeholders.

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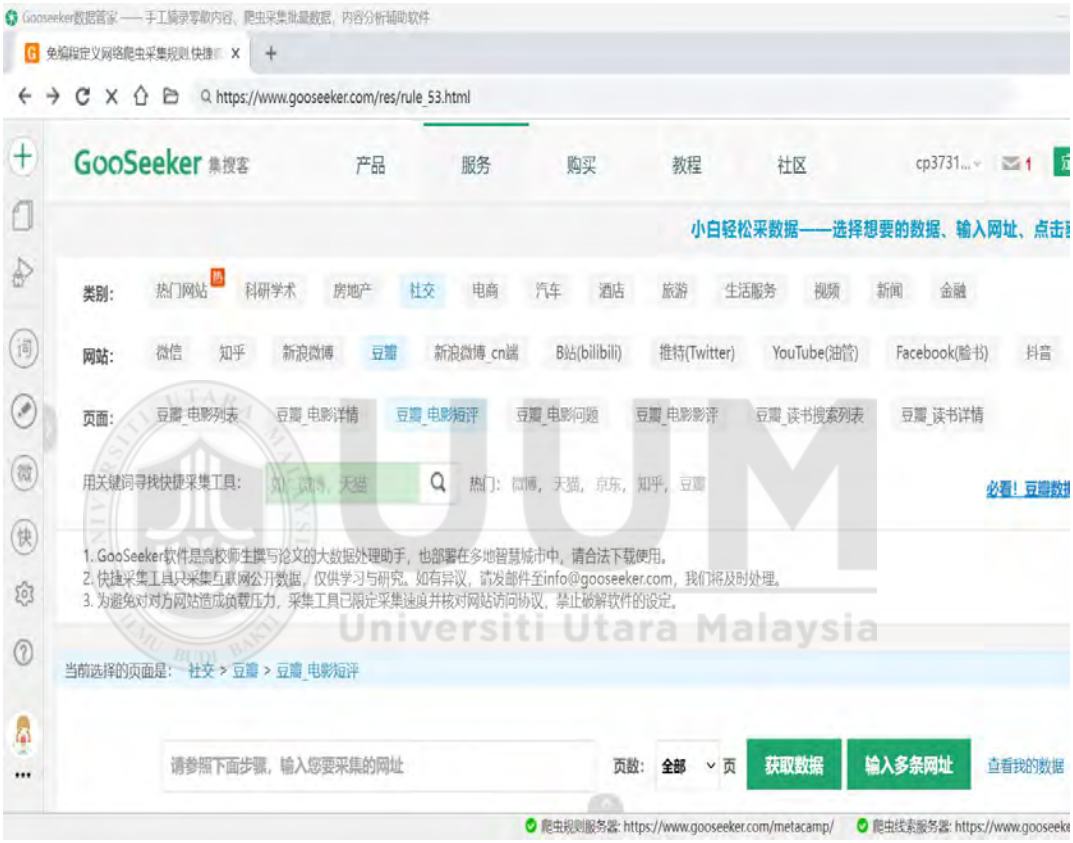
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APPENDICES

Appendix A

The First Process of Big Data Crawling with GooSeeker Software



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Appendix B

The Second Process of Big Data Crawling with GooSeeker Software



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Appendix C

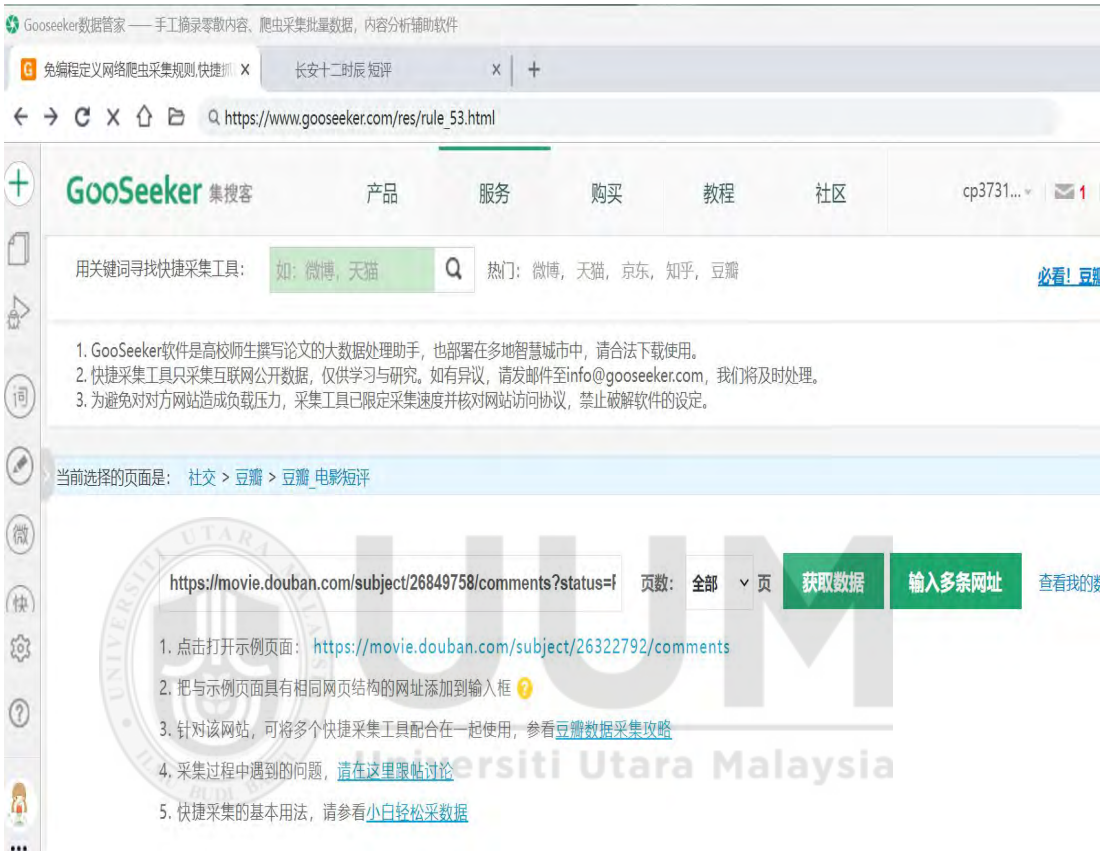
The Third Process of Big Data Crawling with GooSeeker Software



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Appendix D

The Fourth Process of Big Data Crawling with GooSeeker Software



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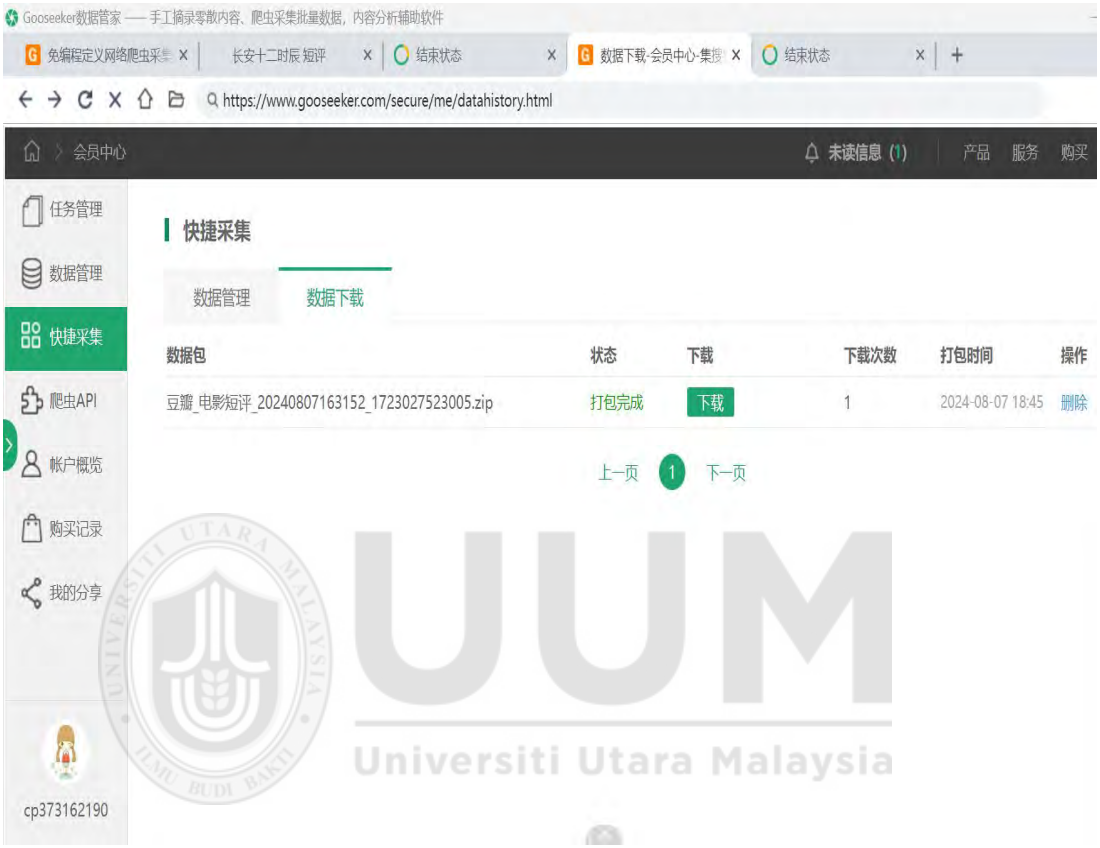
Appendix E

The Fifth Process of Big Data Crawling with GooSeeker Software



Appendix F

The Sixth Process of Big Data Crawling with GooSeeker Software



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Appendix G

The GooSeeker Software's Function of the Measurement of Sentiment Orientation



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Appendix H

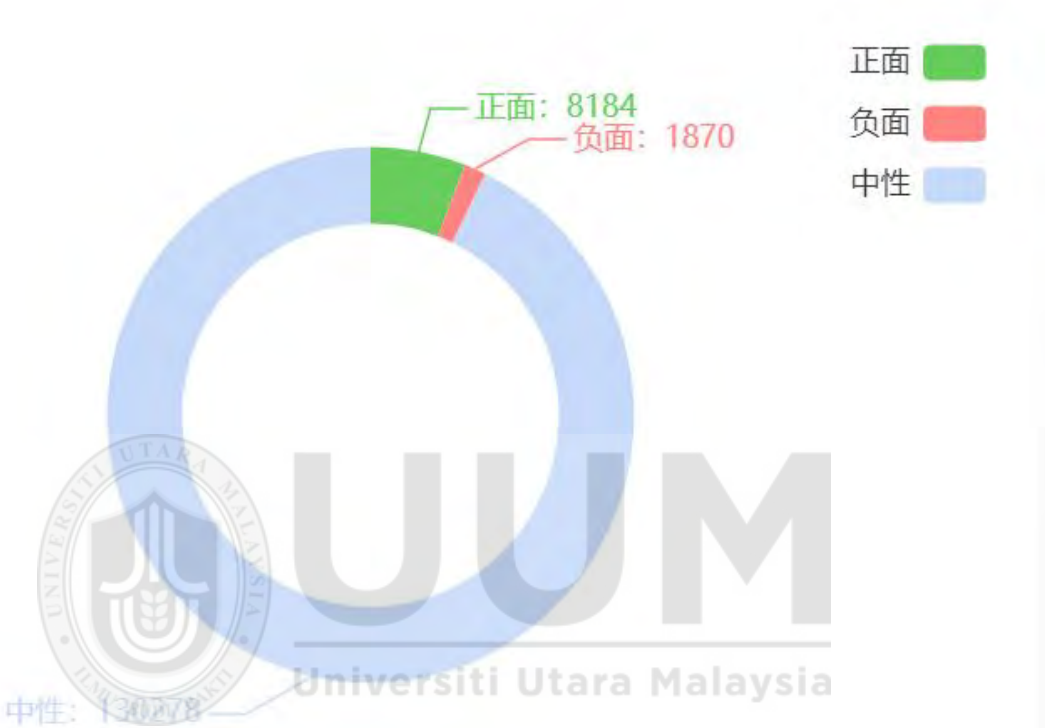
Task Name Input and Data Import



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Appendix I

The Number of Positive, Negative and Neutral Comments for a Certain Web Drama



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Appendix J

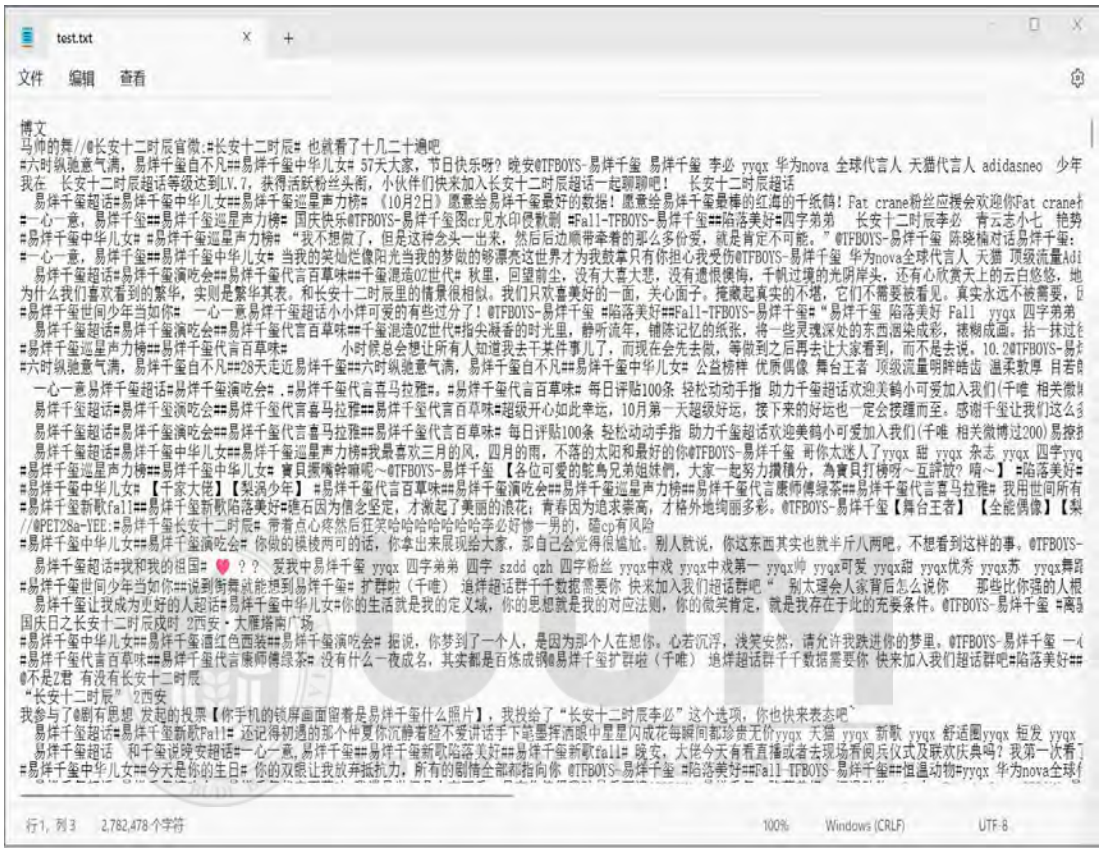
Douban Score for a Certain Web Drama



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Appendix K

The Specified “test” Document Depositing All the Comments



Appendix L

The Instructions of Python Operation

```
1 cmd
2 cd Desktop\test
3 python infer.py
```

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Appendix M

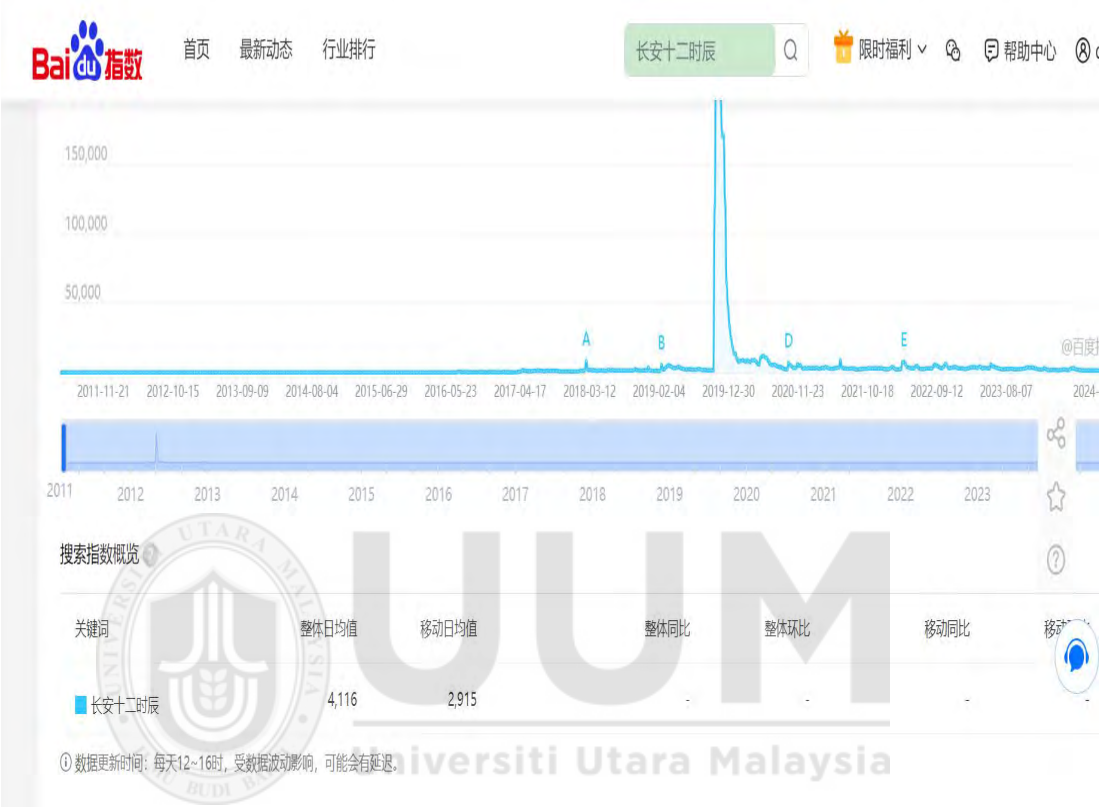
The Illustration of Running Result of Python



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Appendix N

Baidu Search Index of a Given Web Drama



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Appendix O

360 Trend of a Given Web Drama



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Appendix P

Maoyan Popularity Index of a Given Web Drama



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Appendix Q

Maoyan Exposure Volume of a Given Web Drama



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Appendix R

Playback Volume of a Given Web Drama on Chinese TikTok



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Appendix S

Playback Volume of a Given Web Drama on Chinese Kwai



Appendix T

WeChat Index of a Given Web Drama



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Appendix U

Weibo Conversation Volume of a Given Web Drama



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Appendix V

Weibo Interaction Volume of a Given Web Drama



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Appendix W

The Number of Brief Reviews for a Given Web Drama on Douban



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Appendix X

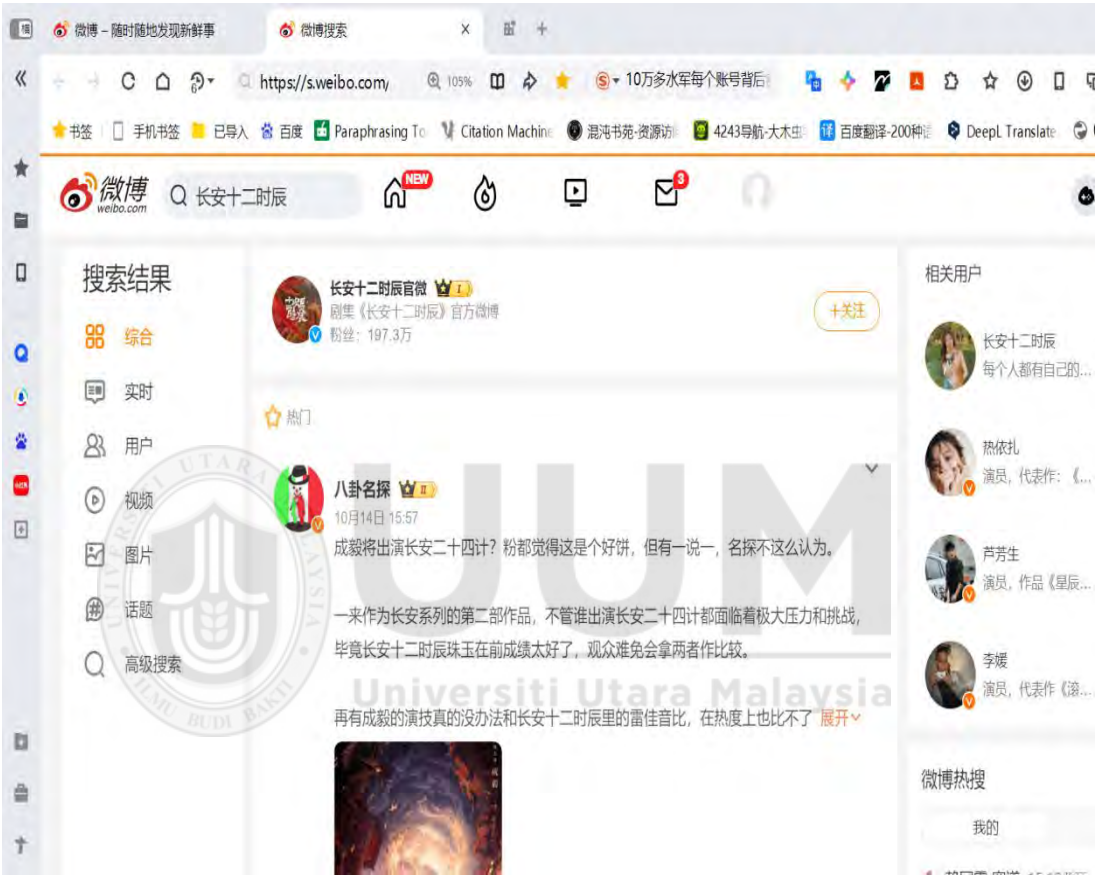
The Number of Comments for a Given Web Drama on Douban



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Appendix Y

The Number of fans on the Official Weibo Account of a Given Web Drama



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