FACTORS INFLUENCING CHINESE CONSUMERS' PURCHASE INTENTION IN LIVE STREAMING COMMERCE

By

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September 2024

Chairman : Norazlyn binti Kamal Basha, PhD
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Live streaming commerce has become a new trend of online shopping, prompting more and more Chinese retailers to embrace this novel channel for product sales. Compared to traditional online commerce, live streaming provides visibility, interactivity, and authenticity, which greatly improve the overall shopping experience and consumer engagement. However, despite the exponential growth of live streaming commerce, many streamers demonstrate low purchase intentions. Responding to the calls of earlier researchers, the main objective of this study was to examine the features that impact live streaming commerce purchase intention among millennial consumers in Mainland China. First, based on the socio-technical theory, streamers' attributes (expertise, physical attractiveness, and interaction orientation) and technical attributes (media richness and personalisation) were suggested as the social and technical factors encouraging purchase intention in live streaming commerce. Second, the Stimulus-Organism-Response (S-O-R) Model was applied to explain the mediating role of swift guanxi. Third, the study examined the moderating role of perceived effectiveness of e-commerce institutional mechanisms (PEEIM). Data was collected using quota

sampling, and the target respondents were Chinese millennials (born between 1981 and 1996) who had shopping experience on live streaming commerce platforms in the past three months. An online questionnaire was distributed to the target respondents via Wenjuanxing. In total, 446 responses were analysed using Partial Least Squares Structural Equation Modeling (PLS-SEM). Three notable findings were identified in this study: (1) purchase intention was influenced by streamer attributes (expertise, interaction orientation) and technical attributes (personalisation); (2) swift guanxi mediated the influences of expertise, physical attractiveness, interaction orientation, and media richness on purchase intention, indicating the indispensable role of swift guanxi; and (3) millennial consumers with a high PEEIM tended to exhibit higher purchase intention toward streamers who have swift guanxi than those with a lower PEEIM. Theoretically, this study contributes to the existing literature by: (1) expanding the application of the socio-technical theory to the context of live streaming commerce; (2) identifying the antecedents and outcomes of swift guanxi in live streaming commerce within the framework of the S-O-R model; and (3) uncovering the mediation process in which streamer attributes and technical attributes affect purchase intention via swift guanxi, based on the S-O-R model; and (4) adding value by exploring the boundary effects of the PEEIM on the relationship between swift guanxi and purchase intentions. Practically, this study suggests that practitioners should adopt the digital trend by utilising both the technical features of live streaming commerce and streamer attributes to improve interpersonal relationships with users, ultimately resulting in positive purchase intentions. Despite the study's interesting findings, several limitations exist. This study focused on Gen Y; therefore, investigating factors influencing purchasing decisions across generations, such as Gen X and Gen Z, is recommended. Additionally, since the study concentrated on a specific country, future research should explore other cultural relational concepts. Researchers should also examine how media richness and purchase intention vary across product categories.

Keywords: Live streaming commerce, Socio-technical theory, Stimulus-Organism-Response model, Swift guanxi, Purchase intention

SDG: GOAL 12: Responsible Consumption and Production

Abstrak tesis yang dikemukakan kepada Senat Universiti Putra Malaysia sebagai memenuhi keperluan untuk ijazah Doktor Falsafah

FAKTOR-FAKTOR YANG MEMPENGARUHI NIAT PEMBELIAN PENGGUNA CINA DALAM PERDAGANGAN PENSTRIMAN LANGSUNG

Oleh

LI YINGXIA

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Pengerusi : Norazlyn binti Kamal Basha, PhD
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Perdagangan penstriman langsung telah menjadi trend baharu dalam pembelian dalam talian dan ini telah mendorong penerimaan peniaga di China dalam menggunakan platform ini untuk menjual produk mereka. Berbanding dengan perniagaan dalam talian konvensional, penstriman langsung menyediakan keterlihatan, interaktiviti dan keaslian, yang meningkatkan pengalaman membeli-belah dan penglibatan pengguna secara menyeluruh. Namun, disebalik pertumbuhan eksponen perdagangan penstriman langsung, terdapat laporan yang menunjukkan niat pembelian dalam kalangan penonton penstriman langsung. Oleh itu, sejajar dengan seruan penyelidik terdahulu, objektif utama kajian ini adalah untuk mengkaji faktor yang mempengaruhi kepada pembelian perdagangan ketika penstriman langsung dalam kalangan pengguna milenial di Tanah Besar China. Pertama sekali, berdasarkan teori sosio-teknikal, kajian ini mencadangkan ciri penstrim(kepakaran, daya tarikan fizikal, dan orientasi interaksi) dan ciri teknikal (kekayaan media dan personalisasi) sebagai faktor sosial dan teknikal yang meningkatkan niat pembelian dalam perdagangan penstriman langsung. Kedua, ia menggunakan Model Rangsangan-Organisme-Tindak Balas (S-

O-R) untuk menerangkan peranan pengantara ‘guanxi’ (rangkaian sosial) pantas. Ketiga, is mengkaji peranan penyederhanaan keberkesanan mekanisme institusi e-dagang (PEEIM). Data dikumpul menggunakan persampelan kuota, dengan menyasarkan golongan milenial di China yang lahir antara 1981 dan 1996, dan mempunyai pengalaman membeli-belah di platform perdagangan penstriman langsung dalam tempoh tiga bulan sebelum pengumpulan data. Soal selidik dalam talian telah diedarkan kepada responden sasaran melalui platform Wenjuanxing.Secara keseluruhan, 446 respon telah dianalisis menggunakan Pemodelan Persamaan Struktur Separa Kuasa Dua (PLS-SEM). Terdapat tiga dapatan signifikan dari kajian ini: (1) niat membeli dipengaruhi oleh ciri penstrim (kepakaran, orientasi interaksi) dan ciri teknikal (personalisasi); (2) guanxi pantas bertindak sebagai pengantara pengaruh kepakaran, daya tarikan fizikal, orientasi interaksi, dan kekayaan media dengan niat membeli, menunjukkan peranannya yang sangat penting; dan (3) pengguna milenial dengan PEEIM yang tinggi lebih cenderung menunjukkan niat pembelian yang lebih tinggi terhadap penstrim langsung yang mempunyai guanxi pantas berbanding mereka yang mempunyai PEEIM yang lebih rendah. Secara teorinya, kajian ini menyumbang kepada literatur sedia ada dengan: (1) memperluaskan aplikasi teori sosio-teknikal dalam konteks perdagangan live streaming; (2) mengenal pasti anteseden dan hasil guanxi pantas dalam perdagangan penstriman langsung dalam rangka model S-O-R; dan (3) mendedahkan kesan pengantaraan di mana ciri pentsrim dan teknikal mempengaruhi niat pembelian melalui guanxi pantas, berdasarkan model S-O-R; dan (4) menambah nilai dengan meneroka kesan PEEIM terhadap hubungan antara niat membel dan ‘guanxi pantas’.Secara praktikalnya, kajian ini mencadangkan bahawa pengamal harus menggunakan aliran digital dengan menggunakan ciri teknikal perdagangan

penstriman langsung dan ciri penstrim untuk meningkatkan hubungan interpersonal dengan pengguna, yang seterusnya dapat mencetuskan niat pembelian yang positif. Kajian ini telah menunjukkan dapatan yang menarik, namun, ia juga mempunyai beberapa batasan. Kajian ini tertumpu kepada Generasi Y dan kajian akan datang disarankan untuk meneliti faktor yang mempengaruhi keputusan pembelian merentas generasi, seperti Gen X dan Gen Z. Selain itu, kajian ini hanya tertumpu pada pengguna di sebuah negara dan kajian akan datang boleh meneroka konsep hubungan budaya yang lain. Penyelidik juga boleh meneliti perbezaan aspek kekayaan media dan niat pembelian merentas kategori produk.

Kata Kunci: Perdagangan penstriman langsung, Teori sosio-teknikal, Model Rangsangan-Organisme-Tindak balas, Guanxi pantas, Niat pembelian

SDG: MATLAMAT 12: Penggunaan dan Pengeluaran Bertanggungjawap

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This thesis was submitted to the Senate of Universiti Putra Malaysia and has been accepted as fulfilment of the requirement for the degree of Doctor of Philosophy. The members of the Supervisory Committee were as follows:

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LIST OF ABBREVIATIONS

URT	Uncertainty Reduction Theory (URT)
S-O-R	Stimulus-Organism-Response (S-O-R)
PEEIM	Perceived Effectiveness of E-commerce Institutional Mechanisms
TAM	Technology Acceptance Model
ELM	Elaboration likelihood model
TRA	Theory of Reasoned Action
eWOM	Electronic word of mouth
HCI	Human-computer interaction
MRT	Media richness theory
MIM	Mobile instant messaging
LBS	Location-based services
AISAS	Attention, Interest, Search, Action, Share
CMC	Computer-mediated communication
B-S	Buyer-to-seller
TPB	Theory of Planned Behaviour
UTAUT	Unified Theory of Acceptance and Use of Technology
CMV	Common method variance
PLS-SEM	Partial Least Square Structural Equation Modelling
VIF	Variance Inflation Factor
HOC	Higher-order construct
HCMs	Hierarchical component models
CB-SEM	Variance-based
LOCs	Lower-order components
CR	Composite reliability

AVE	Average variance extracted
HTMT	Heterotrait-Monotrait
SMEs	Small and medium enterprises (SMEs)

CHAPTER 1

INTRODUCTION

1.1 Introduction

This study investigates the factors that impact the purchase intention of Chinese mainland millennial consumers in live streaming commerce. First, the evolution of e-commerce is discussed. Second, an overview of different types of live streaming commerce and the current status of live streaming commerce in China are presented. Next, the problem statement, research questions, research objectives and significance of study are proposed. Finally, the chapter outlines the scope of study, definitions of terms, and organisation of thesis.

1.2 Evolution of e-Commerce

The widespread popularity of the Internet is driving the growth of e-commerce. Based on the Internet World Stats, global Internet penetration reached 69%, with the number of users reaching 5.5 billion as of December 2022 (Internet World Stats, 2024). Online shoppers surpassed 2.14 billion, constituting 41% of the total Internet user base (Statista, 2022a). This surge in e-commerce has disrupted traditional consumer habits, with online shopping emerging as the preferred mode. Meanwhile, the growth of e-commerce has prompted enterprises to transfer their business online. However, e-commerce has also undergone evolution as technology moves forward (Review & Raimundo, 2021). In general, the development of e-commerce has undergone three stages, including e-commerce, social commerce, and live commerce.

In the 1990s, the emergence of the World Wide Web led to the commercialisation of the Internet, prompting an increasing number of enterprises to establish their websites. This transformation turned the Internet into a powerful business medium, revolutionising global commerce (Ferrera & Kessedjian, 2019; Review & Raimundo, 2021). Enterprises began selling their products through Internet platforms, fostering a significant shift from offline to online retailing and allowing consumers the convenience of shopping at their homes. e-Commerce websites in this period are mainly represented by Alibaba, Amazon, and eBay. By December 2023, global e-commerce sales had reached an impressive $5.8 trillion, with projections indicating an anticipated growth to $7.29 trillion by 2027 (Statista, 2024). Consequently, online shopping has become the preferred mode of shopping for consumers.

With the increasing popularity of social media and the advancement of Web 2.0 technologies, the convergence of these innovations with traditional e-commerce has given rise to a new business model known as social commerce. As a subset of e-commerce, social commerce emerged from the notion that e-commerce could leverage social media and Web 2.0 technologies to achieve various objectives, including promoting collaboration among customers, enhancing relationships with consumers, and extracting economic value (Kim & Srivastava, 2007). Classic social commerce is represented by social networking sites such as Facebook, Instagram, and China's Sina Weibo and Xiaohongshu. Social commerce introduces a new method for consumers to communicate and exchange product information, which further influences their purchase decisions (Hyun et al., 2021; Xue et al., 2020).

In the late 2000s, the emergence of the Semantic Web ushered in the era of smartphones and mobile applications. As a result of the technological revolution at the forefront of the Internet, computer-mediated forms of communication have evolved beyond static text and images, to embrace richer mediums such as audio and video. Specifically, live streaming has evolved as a novel form of social media, involving the simultaneous distribution of video content to diverse audiences through video streaming technology (Chen & Lin, 2018; Hu et al., 2017). Users can watch the content in real-time without waiting for the entire file to be completed (Cheng et al., 2019; Zhao et al., 2018), enabling the audience to "feel like they are present at the event" (Chen & Lin, 2018). An increasing number of social media platforms are also utilising live streaming features, such as Twitter, Facebook, Instagram, and YouTube. Of these, Facebook receives 8 billion live streaming visits per day and three times as many live video views as non-live video views (Todd & Melancon, 2018). The global live streaming market is predicted to expand from $30.29 billion in 2016 to $534 billion by 2030 (Market Research Future, 2022). In addition, live streaming is particularly popular among younger generations, where in China, about 75% of live streaming users are under the age of 36 (Hou, Li, et al., 2020).

Simultaneously, with the maturation of Wi-Fi and 4G/5G technologies, smartphones and online payment methods are becoming more prevalent. Given the huge potential of live streaming, the Chinese e-commerce giant, Taobao, integrated live streaming into its business in 2016 to enhance user engagement (Statista, 2022a). Its main competitor, JD, subsequently also added the live streaming feature (Statista, 2022a). Over the following years, the transformation of live streaming for e-commerce swept the world. In 2017, Alibaba extended its live-streaming service to Russia.

Subsequently, Alibaba's Lazada incorporated a live streaming feature in Malaysia, the Philippines, and Thailand, enabling sellers to interact directly with users. In Japan, flea market apps Mercari and Rakuten embraced the live-streaming function (Jakobsen, 2021). In the U.S., Amazon joined the livestream trend in January 2019 (Jakobsen, 2021). Notably, major social media platforms such as Facebook, YouTube, and Instagram have also integrated purchase links via live streaming (Statista, 2022a). Now, sellers around the world are increasingly using live streaming as a novel direct interaction channel for selling a diverse range of products (Wongkitrungrueng & Assarut, 2020). Live streaming is emerging as an indispensable sales channel, providing sellers with the opportunity to win or solidify their competitiveness in a highly competitive marketplace (Coresight Research, 2022).

The "watch now, buy now" sales approach introduces a fresh consumer experience (Xue et al., 2020). Specifically, compared to other forms of commerce, live streaming commerce exhibits four notable distinctions (see Table 1.1). Firstly, it can convey product information more comprehensively and intuitively, making it easier for users to make purchase decisions. Traditional e-commerce primarily displays products through static pictures, which are easily editable and less effective for product evaluation (Benedicktus et al., 2010). In contrast, live streaming commerce presents products in the form of videos, which is proving to be more accurate and efficient in conveying information compared to the traditional online shopping experience with pictures and text displays (Gao et al., 2021; Wongkitrungrueng & Assarut, 2020). Thus, products are also easier to evaluate for live streaming commerce consumers.

Secondly, live streaming commerce offers more efficient interactions. Compared to traditional e-commerce that relies on customer service and the lagging interaction mode of user comment feedback, live streaming commerce supports real-time interaction among all viewers and streamers (Sun et al., 2019; Xu et al., 2020). Consumers can ask questions to streamers and share their purchasing experiences with co-viewers at any time. Meanwhile, information feedback is more rapid, accurate, and personalised, which can help consumers make purchasing decisions more effectively (Sun et al., 2019). Users can evaluate streamers and products through co-viewers' engagement behaviours, such as likes, pop-up comments, and purchases activity (Ma, 2021b). Information and emotions derived from viewers' interactions within the live streaming room can influence product sales through indirect or direct perceptions (Fei et al., 2021; Lin et al., 2021; Xue et al., 2020).

Thirdly, the visibility of live streaming commerce allows the streamer's attractiveness, personality, and expertise to be recognisable, potentially influencing users' emotions, perceptions, and behaviours (Cheng et al., 2019; Hou, Guan, et al., 2020; Zhu et al., 2021). The streamers can present consumers with comprehensive details of a product, highlighting its advantages through diagnosis and vicarious expression (Li et al., 2021; Lo et al., 2022). Taking apparel products as an example (see Figure 1.1), the streamer can match the apparel on the spot, better showcasing the products and enhancing consumers' shopping experience.

Fourthly, the method of obtaining goods of interest differs (iiMedia, 2022; MOF, 2021). In traditional e-commerce, consumers acquire products of potential interest through keyword searches. The product is then evaluated, and a purchase decision is made, resulting in a longer product decision cycle. In contrast, live streaming commerce shortens the decision cycle as it enables users to quickly find products of interest through personalised recommendations from platforms and live streamers.

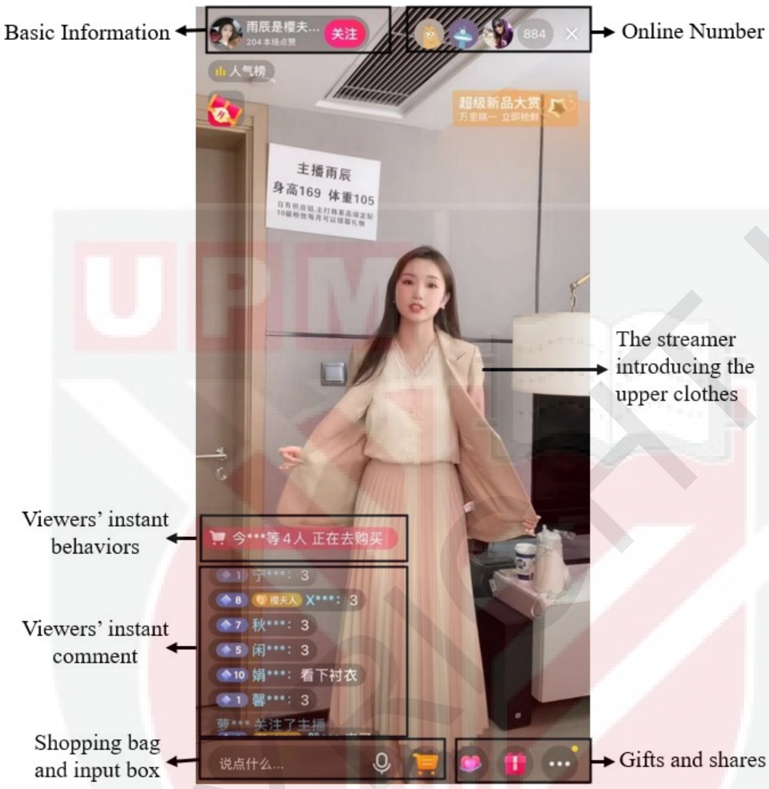

Figure 1.1 : Interface and Elements of Live Streaming Commerce

In summary, online commerce has evolved from the hypertext era (traditional e-commerce) to the social era (social commerce) and the current semantic era, characterised by live streaming commerce. This evolution has profoundly changed the way sellers promote their products. Live streaming enables sellers to directly communicate with customers and offer more personalised recommendations than in earlier periods (Chen et al., 2019; Sun et al., 2019). The growth of live streaming commerce undeniably provides customers with a unique buying experience, enhancing interaction and customisation (Wongkitrungrueng et al., 2020). This emerging platform has significantly transformed the competitive landscape, making it an appealing and relevant topic for further research.

Table 1.1 : Comparison of Live Streaming Commerce with other Forms of Commerce

Offline	e-Commerce	S-commerce	Live commerce
Spatially adjacent (Kozlenkova et al., 2017)	Physical and temporal isolation (Pai & Tsai, 2011)	Physical and temporal isolation	Spatial isolation but temporal closeness
Face-to-face communication	Text communication. Insufficient verbal and nonverbal (Benedicktus et al., 2010)	Like, comment	Bullet comments, lianmai, text, picture, live videos
Buyer-seller' identity is observable	Limited information is available on the identities of the buyer-seller	Limited information is available on the identities of the buyer-seller	Identity of sellers is observable
Evaluation of a product is operated by the five senses	Product evaluation is challenging. Photos are editable.	Product evaluation is improved with social media construct (Rating and reviews).	Product evaluation is easier with live video
Synchronous one-to-one or one-to-may interaction	Interaction with a single customer via chat box	One to one communication through chat box, instant message, feedback system	Simultaneous one-to-many interaction
Limited search+ discovery	Search	Discovery	Discovery

(Source: Wongkitrungrueng et al., 2020)

1.3 Types of Live Streaming Commerce

This section discusses the classification of live streaming commerce, which can be categorised into three groups (see Table 1.2). The first category includes traditional e-commerce platforms incorporating live streaming services (e.g., Taobao and JD) (Cai & Wohn, 2019). Live streaming serves as an alternative method to comprehensively display products within this category of live streaming commerce. Users entering the live room on these platforms can gain a better understanding of the products and access information regarding discounts (Cai & Wohn, 2019). Major traditional e-commerce platforms like Amazon and Taobao have integrated live streaming services as a means to expand new sources of traffic and increase consumer engagement (Wongkitrungrueng et al., 2020).

The second category involve social service platforms that incorporate live streaming features for selling (e.g., Wechat). Social service media are platforms that support user-to-user social network building (Lin et al., 2019). These platforms provide rich media features to share information and easily connect with others, offering instant video and voice chat functions. Users can share text, photos, and videos, and they can also give ‘thumbs up’ to others’ posts (Fan et al., 2019; Shao & Pan, 2019). Additionally, social service platforms can effectively guide users in sharing and acquiring traffic at a relatively low cost. Platforms represented by WeChat added an e-commerce function in 2020, and these platforms are still in the initial stage of development.

The third type is the integration of content sharing platforms with live streaming sales (e.g., Facebook and Douyin) (Wongkitrungrueng et al., 2020). Content-based social media platforms are designed for sharing personal life, knowledge, products, and entertainment through content creators (Tajvidi et al., 2020). In addition, due to its diverse content types and advanced recommendation algorithms, the content platform has seen rapid growth in its number of users, who have demonstrated a high degree of stickiness. For example, the per capita daily usage hours of Douyin and Kuaishou are 108 minutes and 102 minutes, respectively (QuestMobile, 2022). From the platform’s perspective, content-based platforms seek to enhance the value of user traffic by incorporating live streaming features. From the streamers' perspective, beyond product display, live streamers can leverage the social attributes of these platforms to establish a "streamer-consumer" relationships, thereby gaining consumption value.

In general, live streaming commerce includes both the social nature of live streaming and the marketing nature of an e-commerce. Specifically, as a subcategory, live streaming commerce in content sharing platforms is becoming a new trend in the industry, leveraging the inherent advantages of a robust user traffic base and high stickiness.

Table 1.2 : Categories of Live Streaming Commerce

No.	Category	Platform
1	e-Commerce Platform	Amazon; Taobao; JD; Pinduoduo; VIP
2	Social Service Platform	Weibo; WeChat
3	Content sharing Platform	Facebook; Instagram; YouTube; Douyin (TikTok); Kuaishou (Kwai)

(Source : Cai & Wohn, 2019; MOF, 2021; Wongkitrungrueng et al., 2020)

1.4 Overview of Live Streaming Commerce in China

Live streaming commerce is gaining increasing attention from users in China (Chen et al., 2020). As of June 2023, China boasts 1.079 billion Internet users and 1.007 billion social media users, with an Internet penetration rate of 76.4% (CNNIC, 2022, 2023). Furthermore, the number of live commerce users in China has hit 526 million, constituting 48.8% of all Internet users (CNNIC, 2023). China's large user base, high penetration rate, and the rapid expansion of social media provide a solid foundation for the growth of live streaming commerce. Notably, China's live streaming commerce reached $179 million in 2021 (see Figure 1.2).

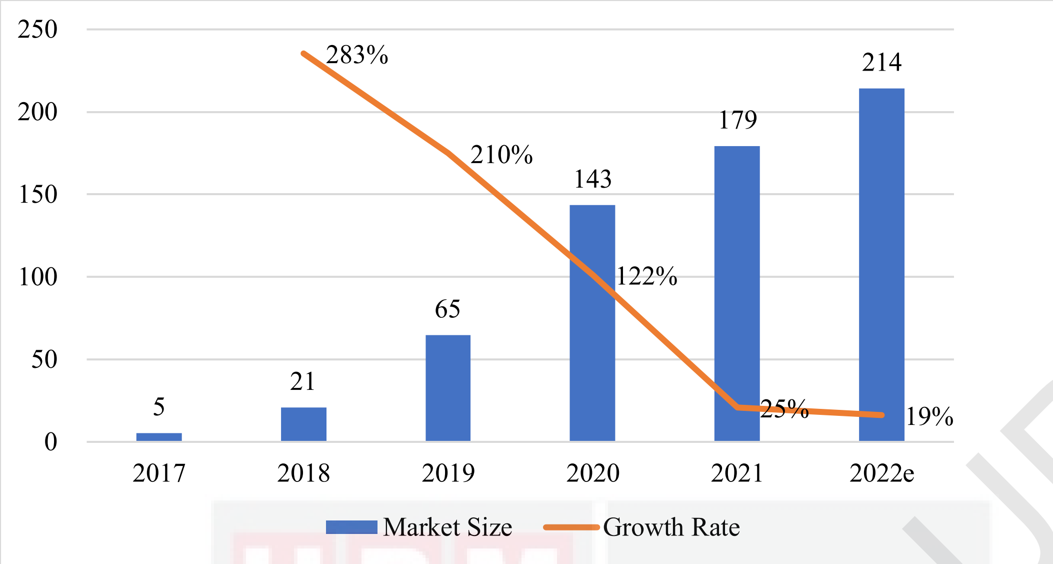

Figure 1.2 : Market Size of China's Live Streaming Commerce from 2017 to 2022 (Billion Dollars)
(Source : iiMedia, 2023; MOF, 2021)

Live streaming, as a marketing channel, has brought significant changes to the online marketplace. It enables brands and suppliers to reduce operational costs, directly interact with users to better understand market needs, and attain a higher market position. Many reports on live-streaming commerce emphasise its potential to provide a profitable sales channel for enterprises. Notably, over 100,000 brands and suppliers in China already leverage live streaming to promote their products (CNNIC, 2021). They recognise that live streaming not only drives online sales but also directs traffic to their offline stores, enhancing stickiness through live streaming interactions (CNNIC, 2021). Both national brands (e.g., Lin Qingxuan, Xiaolongkan) and international brands (e.g., Uniqlo, L'Oreal) have embraced live streaming, collaborating with independent streamers to sell their products or establish their own branded live streaming rooms. According to the Ministry of Commerce, more than 60% of brands have attracted new customers and promoted products and services through live streaming (MOF, 2021). Furthermore, over 70% of brands have reported increased sales through live streaming (MOF, 2021).

However, despite its rapid growth, live streaming commerce faces several criticisms. Firstly, there is widespread false advertising; reports indicate that 39% of surveyed users have encountered misleading promotions (iiMedia, 2022). Some streamers exaggerate product effectiveness, fabricate market share claims, and forge user reviews to boost sales. Secondly, the live streaming commerce market lacks adequate regulation. Given its recent emergence and rapid expansion, relevant laws are still insufficiently developed and enforced (CCA, 2023). Additionally, the integration of product promotion within live streams complicates the extraction of direct evidence for illegal advertising, as current technology struggles to capture dynamic video content in real time (CCA, 2023). Lastly, the allocation of responsibility is unclear, as live streaming commerce involves multiple stakeholders—including streamers, MCN agencies, merchants, and platforms—leading to gray areas in after-sales responsibility when product issues arise (CCA, 2023). These behaviours infringe on the interests of consumers and harm the healthy development of the live streaming commerce industry.

The report released by the Ministry of Finance (2021) illustrates that Taobao, Douyin, and Kuaishou are the three largest live streaming commerce platforms in China, collectively accounting for more than 90% of China's live commercial industry (see Figure 1.3). Taobao, with its traditional e-commerce advantage, holds the largest market share of live streaming commerce. However, content-sharing platforms, represented by Douyin, are changing the market landscape with their large user base and user stickiness (see Table 1.3). Occupying users' fragmented time, both Douyin and Kuaishou had a per capita single-day usage time of nearly 110 minutes in March

2022, while Taobao's per capita single-day usage time was only 22 minutes during the same period (Chanmama, 2022). Specifically, Douyin, Kuaishou, and Xiaohongshu emerge as the major players in the content-sharing domain.

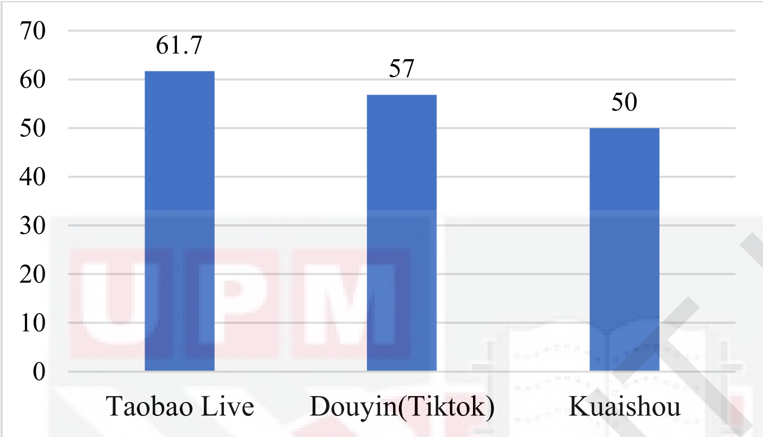

Figure 1.3 : Sales of China's Major Live e-Commerce Platform in 2020 (billion dollars)
(Source : MOF, 2021)

Table 1.3 : Active Uses and Market Share in Different Live Commerce Platform

Live Commerce Platform		Platform Active Users (Million/per Month)	Average Usage Time (Min/per Day)	Users/All live Commerce Users
e-Commerce Platform	Taobao	870	22	68.5%
	Tmall	794	15	32.4%
	JD	440	18	23.8%
	Pinduoduo	630	25	20.9%
	VIP	42	10	12.0%
	Mojujie	1.73	16	8.5%
Content Sharing Platform	Douyin	680	108	57.8%
	Kuaishou	390	102	41%
	Xiaohongshu	200	66	19.5%

(Source: CCA, 2020; Chanmama, 2022)

Douyin (or TikTok as the international version) is a short video platform and is the most downloaded app globally in 2021. As of April 2022, Douyin boasts more than 600 million active daily users in China. In 2020, the total Gross Merchandise Transaction (GMV) of Douyin Live Commerce surpassed $57 billion, more than three times that of 2019 (iiMedia, 2022). Douyin Live includes several features. It offers pop-up features that enable users and streamers to interact with each other and among users. Additionally, it provides a one-click clear screen feature, allowing users to view a more comprehensive display of the product or service (see Figure 1.4). Reports indicate that the average purchase rate of Douyin Live is between 1% and 2%, with most product categories falling below 2% (see Figure 1.5).

Figure 1.4 : Live App: Douyin (Tiktok) Live

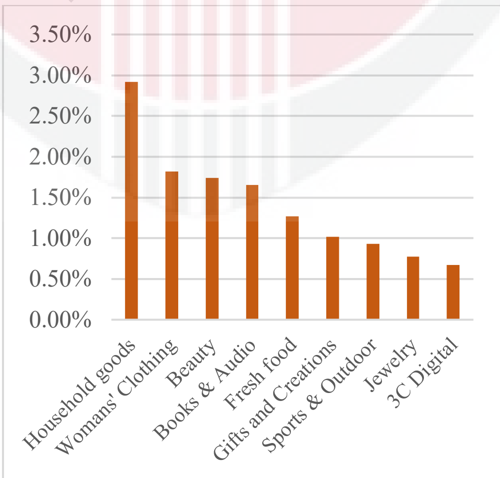

Figure 1.5 : Purchase Rate of Different Product Categories in Douyin Live
(Source: Feigua, 2022)

Next, Kuaishou is a short video platform with 400 million monthly active users.

Kuaishou debuted its e-commerce feature in 2018, enlisting considerable streamers to promote various commercial activities (Cai & Wohn, 2019). Kuaishou’s streamers often call viewers as "homie" or "Laotie" and are dedicated to cultivating Laotie relationships with their audience. Furthermore, Kuaishou provides unique features. For example, users can view the product details page and place one-click orders for live products without exiting the live room (see Figure 1.6).

Figure 1.6 : Live App: Kuaishou Live

The streamer is the core and content creator of live streaming commerce (Hsu et al., 2020; Zhang et al., 2022). Streaming has been recognised as a new profession by the Ministry of Human Resources in China (CCA, 2020). 84% of users admitted that they would purchase products recommended by streamers and are more willing to purchase from streamers with whom they have a good relationship. The term “Lao tie” (similar to homie), is a specific term to represent the close relationship between streamer and consumer (MOF, 2021).

In terms of attribution, streamers can be categorised into independent and branded streamers (Xu et al., 2020). Independent streamers refer to those who conduct live streaming independently without relying on MCN organisations or merchants. In contrast, branded streamers are employed by merchants to sell products on branded live channels. Branded streamers have become a prominent trend, where in 2021, their turnover accounted for nearly 55% of the entire live streaming business (iiMedia, 2022).

Based on the number of followers, streamers can be categorised into top streamers (30 million followers or more), medium streamers (1-30 million followers), and small streamers (less than 1 million followers) (iiMedia, 2022). The Matthew effect refers to a pattern in which those who are initially advantaged achieve greater social or economic success over time, while those who are initially disadvantaged become more disadvantaged over time (Merton, 1968). The Matthew effect is evident in the live streaming business, as top streamers only account for 2.16% of the total number of streamers but occupy nearly 80% of the market share. Meanwhile, small and medium-sized streamers, constituting 90% of the market, often face challenges in sustaining their presence (Guo et al., 2022; iiMedia, 2022). In addition, negative news about streamers has garnered attention. For instance, Kuaisohou's top streamer Simba was exposed for selling fake bird's nests, and Douyin's top streamer Crazy Xiao Yang faced accusations of false propaganda (iiMedia, 2022).

In conclusion, live streaming commerce offers brands and retailers a valuable opportunity to enhance competitiveness and solidify their position in the marketplace. Understanding consumers' purchase intention in live streaming commerce is crucial, given its significant role in winning the online market. China's high e-commerce penetration and leading position in live streaming commerce make it an ideal landscape for studying this emerging trend. Additionally, the substantial user base and stickiness of content sharing platforms have reshaped the competitive landscape of online marketing, making research in live streaming commerce for such platforms a meaningful exploration. Two well-known live streaming commerce applications have indicated that well-designed functional systems and effective streamer characteristics may be key to success in this domain. The significance of live streaming commerce technology and streamer attributes point scholars towards investigating the role of technical and streamer attributes in the live streaming commerce environment.

1.5 Culture and Guanxi in China

Confucianism is an ethical, religious, and philosophical system that has long dominated cultures in East and Southeast Asia, including China, Korea, Japan, and Vietnam (Wang, 2007a). Founded by Confucius (551-479 BCE), one of the most influential philosophers and educators during China's Spring and Autumn period (approximately 771-476 BCE), Confucianism has served as a guiding ideology since the Han Dynasty (206 BCE - 220 CE) and has significantly influenced the daily lives and business practices of Chinese people for thousands of years (Farh et al., 1998; Lee & Dawes, 2005; Wong & Tam, 2000).

The core of Confucian values is "ren", meaning "benevolence" or "loving others." This principle serves as a moral guideline for interpersonal relationships, emphasising that people should treat others with kindness to foster harmonious and friendly interactions (Wang, 2007). It posits that through harmonious relationships, society as a whole can become more tolerant and stable (Arias, 1998; Farh et al., 1998). Under this Confucian social theory, the Chinese place a high value on interpersonal connections, leading to a culture that thrives on "guanxi", which reflects the importance of social ties (Fan et al., 2019; Ou, Pavlou, & Davison, 2014).

Confucianism also underscores that all relationships begin with familial ties, which serve as the foundation for all interpersonal connections (Lin, 2011). It emphasises that individuals are inherently linked to their families, with veneration of ancestors taking precedence over other relationships, highlighting the family-oriented values within Chinese culture (Chen & Eweje, 2019). Viewed from this perspective, Confucian culture can be interpreted as a clan-based culture, where interpersonal relations and social order are maintained through kinship and emotional bonds (Yeung & Tung, 1996). Unlike the individualistic culture seen in Western societies, which focuses on distinct roles, Chinese society prioritises the family unit (Yeung & Tung, 1996). Thus, family relationships often take precedence over other social ties formed through contracts. Consequently, the phenomenon of "guanxi" typically starts within the family and expands outward to acquaintances (Lin, 2011). Due to a general mistrust of strangers, Chinese people tend to place their trust in those within their inner circle rather than outsiders. In summary, Chinese culture is deeply influenced by Confucianism, which emphasises interpersonal relationships, especially among family members. China is characterised as a relationship-oriented society, where guanxi are viewed as crucial social resources (Farh et al., 1998; Lin, 2011; Yeung & Tung, 1996).

The rise of social media has transitioned guanxi from offline to online. People use the interactivity and richness of social media to expand their networks (Shao & Pan, 2019).

In the context of e-commerce, Taobao sellers utilise online interactive tools to quickly establish guanxi with users, which has been shown to be a key factor in driving sales growth (Ou, Pavlou, & Davison, 2014). In live streaming commerce, face-to-text interaction facilitates relationship building. Streamers refer to their viewers as "brothers" or "homies," attempting to forge guanxi akin to that between friends or relatives (Chen et al., 2022). Understanding the role of guanxi in live streaming commerce offers opportunities to further explore user behaviour.

1.6 Problem Statement

Since 2016, live streaming commerce has become a new mode of shopping, with more and more Chinese merchants using live streaming for marketing. For example, the report revealed that more than 100,000 brands and vendors had used live streaming commerce to promote their products in 2020, which has also driven 1.23 million streamers to join live streaming commerce, with a growth rate of 348% compared to 2019 (MOF, 2021). Besides, CTR's brand survey illustrated that 48% of advertisers plan to increase their investment in live streaming in 2022. In particular, 66% of advertisers plan to invest in content sharing platforms (CTR, 2022). Likewise, in China, the future of the online marketplace is predicted to be driven by live streaming commerce, as live streaming commerce shoppers have reached 526 million, accounting for 48.9% of all Internet users (CNNIC, 2023). This trend is foreseen to grown rapidly. As a result, a growing number of Chinese merchants are interested in using live streaming commerce as a new sales channel to acquire a competitive advantage and improve their market position.

Although live streaming commerce has shown considerable growth in the industry, many streamers struggle to convert viewers into consumers. An industry report conducted by Questmobile revealed that the average purchase rate for live streaming commerce ranges between 1% and 2% across most product categories, including women's apparel, beauty and 3C digital (QuestMobile, 2022). Besides that, the report further illustrated that the average time users spend in a live room is merely 85 seconds, indicating that users enter the room and then leave quickly. Thus, streamers cannot form connections and convert viewers into buyers (Chanmama, 2022). In other words, this indicates that only few streamers understand how to achieve their marketing goals through live streaming. In fact, several industry reports have continually presented this issue. For instance, a report conducted by iiMedia revealed that 72.6% of users are concerned about the streamer's credibility and thus are reluctant to purchase. Of these, 30.8% of users have experienced exaggerated propaganda by streamers (iiMedia Research, 2020). Besides that, more than 40% of users are reluctant to purchase due to the low quality of the content. The similarity between the live product presentation and product content result in viewers experiencing aesthetic fatigue (iiMedia, 2022). Also, the average length of stay of users in live streaming rooms is short. If a streamer fails to quickly attract users and establish a connection with them, viewers are likely to switch to other streamers. In other words, increasing the purchase rate of live streaming commerce has become a complex task for both platforms and streamers, especially when they can easily switch between live channels (CNNIC, 2022; Kim & Kim, 2022).

However, previous studies provide insufficient information for streamers and sellers to implement effective strategies, especially in identifying factors that drive users' purchase intention. As an emerging and rapidly developing sales model, existing studies on live streaming commerce are still in the initial stage (Guo et al., 2021; Lee & Chen, 2021; Sun et al., 2019; Xue et al., 2020). Previous literatures on live streaming commerce mainly focus on consumers' motivation to engage (Lin et al., 2021; Liu et al., 2021; Wongkitrungrueng & Assarut, 2020; Xue et al., 2020), driving factors of attitude, and satisfaction (Li et al., 2021; Ma, 2021a). Although these studies provide useful insights into the field of information systems and marketing, studies on the factors influencing users' purchase intention are still insufficient, forming a gap in literature. Thus, this study examines the factors driving millennial users' live streaming shopping intention. The literature review revealed four literature gaps that need to be addressed in the current context.

First, while some of the factors driving purchase intention in the context of live streaming commerce have been theorised, there is a lack of a comprehensive theory to identify the factors that drive users' purchase intentions in live streaming commerce. Ma (2021b) pointed out that social and technical factors need to be integrated to fully understand live streaming commerce. Similarly, Kim et al. (2022) argue that previous research has yet to consider the joint role of streamer attributes and technical (platform) attributes to form positive outcomes, especially in the context of live streaming commerce. This notion is supported by the socio-technical theory, which proposes that social and technical systems should be combined together to drive economic optimisation for the system (Trist et al., 1963). Users not only interact with streamers; they also interact with the technical platforms in live streaming commerce. Therefore, the socio-technical theory was chosen as the underpinning theory for identifying the key driving factors in live streaming commerce. Combining these insights, it is likely that the streamer's attributes (expertise, attractiveness, and interaction orientation) and technical attributes (media richness and personalisation) are important factors that help increase purchase intention in live streaming commerce.

Secondly, researchers have called for further research on the unique relational features of Chinese culture, which may trigger the success of social commerce (Ma, 2021b; Sun et al., 2019). The existing literature mainly emphasised on the relational exchange in the Western context, manifested as trust, satisfaction, and commitment. Relational exchange is guided by laws and rules (Ou et al., 2014; Wang, 2007). However, China differs from Western culture in its inadequate institution, legality and the influence of Confucian values (Ou, Pavlou, & Davison, 2014). China is heavily influenced by Confucianism, which emphasises the importance of building harmonious "guanxi" (Bilal et al., 2022; Wong & Tam, 2000). Within this context, swift guanxi, a quickly formed intimate and caring interpersonal relationship, has been widely recognised as a key to success in the Chinese online marketplace (Ou & Davison, 2014; Shi et al., 2018). Live streaming commerce enables the development of swift guanxi through real-time communication, which can reduce uncertainty and encourage purchasing behaviour (Bründl et al., 2017; Ng, 2013). Therefore, swift guanxi is likely an important contributor to purchasing behaviour in live streaming commerce. However, swift guanxi has not received enough attention in live streaming commerce research (Chen et al., 2021; Lin et al., 2019). In particular, research examining the antecedents and the outcomes of swift guanxi remains sparse in live streaming commerce (Chen et al., 2021; Lin et al., 2019; Sun et al., 2019). Furthermore, Fan et al. (2019) called for the exploration of the combined effects of social and technical factors on swift guanxi. This notion is consistent with the socio-technical theory, which provides a helpful framework for identifying streamers and technical-related factors. Yet, there is scant research that examines the relationship between streamer attributes, technical attributes, and swift guanxi in the live streaming commerce (Shao & Pan, 2019). Thus, this study empirically examines the relationship between streamer attributes, technical attributes, swift guanxi, and the influence of swift guanxi on purchase intention in live streaming commerce, further enriching the understanding of this new paradigm of swift guanxi. The stimulus-organism-response (S-O-R) model by Mehrabian and Russell (1974) supports the understanding of these relationships.

Third, previous technical literature has only examined the direct relationship between the factors and users' purchase intention. The underlying mechanisms of how these factors influence user behaviour are unclear (Cai et al., 2018; Hou et al., 2020). Ou et al. (2014) recognised swift guanxi as a crucial mediator to investigate customer behaviour. Previous studies have also consistently investigated the mediating effect between technical characteristics, interpersonal factors, information quality, and favourable outcomes in the online marketplace (Cheng et al., 2020; Fan et al., 2019; Lin et al., 2017). However, there is a paucity of studies on the mediating role of swift guanxi that link digital attributes and decision-making in live streaming commerce (Lin et al., 2017). Thus, this study goes beyond the direct influence of factors on purchase intention and explores their indirect effects through consumers' swift guanxi with streamers. Mehrabian and Russell's (1974) S-O-R model also supports the understanding of the mechanisms by which streamer attributes and technical attributes drive swift guanxi and ultimately lead to purchase intention.

Lastly, while the literature highlights the importance of institutional mechanism (e.g. PEEIM) in online consumer behaviour (Chen et al., 2021; Wongkitrungrueng &

Assarut, 2020; Zhang et al., 2020), there is little relevant empirical research in the live streaming commerce sector, resulting in a clear theoretical gap. An individual may react differently depending on their perception toward the e-commerce institutional mechanisms (Dong & Wang, 2018). The Uncertainty Reduction Theory (URT) suggests that individuals use passive, active or interactive strategies to reduce uncertainty, thereby increasing the predictability of outcomes. High PEEIM can function as an active strategy to reduce uncertainty, as buyers perceive explicit regulatory assurances as aimed at mitigating environmental uncertainties (e.g., leaking of personal information, credit card fraud) (Fang et al., 2014). Consequently, users are more inclined to develop positive responses (Han & Li, 2021). In such a stable trading environment, buyers with positive interpersonal relationships with sellers are more likely to be willing to purchase, as this further reduces the user's uncertainty perception from a different perspective. Meanwhile, when the PEEIM is low, even though the relationship with the seller reduces the risk regarding the seller or the product, the user's risk regarding the transaction environment independent of the seller, such as privacy issues from the platform, may still affect the user's purchase intention (Chen et al., 2022; Tandon et al., 2021). Similarly, PEEIM may also influence the relationship between swift guanxi and purchase intention. Therefore, this study proposes PEEIM as a potential moderator based on URT to investigate changes in users' purchase intentions that may arise from swift guanxi.

In general, this study intended to identify the factors that influence live streaming shopping intention. Underpinned by the S-O-R model and socio-technical theory, streamer attributes and technical attributes are proposed as stimulus factors, and swift guanxi is suggested as the mediator that could improve live streaming shopping intention. Meanwhile, PEEIM is proposed as the moderator that influences the relationship between swift guanxi and purchase intention.

1.7 Research Questions

To fill the research gaps identified in the previous section, this study aimed to investigate how streamer attributes and technical attributes influence live streaming shopping intentions among millennial shoppers in China. Specifically, five distinct research questions were examined:

i. Do streamer attributes and technical attributes of a live streaming platform influence purchase intention among millennial live streaming shoppers in China?

ii. Are there relationships between streamer attributes, technical attributes, and swift guanxi among millennial live streaming shoppers in China?

iii. Does swift guanxi lead to purchase intention among millennial live streaming shoppers in China?

iv. Does swift guanxi mediate the relationship between streamer attributes, technical attributes, and purchase intention among millennial live streaming shoppers in China?

v. Does PEEIM moderate the relationship between swift guanxi and purchase intention among millennial live streaming shoppers in China?

1.8 Research Objectives

The main objective of this study is to investigate factors that influence viewers' live streaming shopping intentions. The following are the specific objectives:

1. To evaluate the influence of streamer attributes and technical attributes on purchase intention among millennial live streaming shoppers in China.

2. To examine the influence between streamer attributes and technical attributes on swift guanxi among millennial live streaming shoppers in China.
3. To examine the influence of swift guanxi on purchase intention among millennial live streaming shoppers in China.
4. To assess the mediating effect of swift guanxi between streamer expertise, technical attributes and purchase intention among millennial live streaming shoppers in China.
5. To evaluate the moderating effect of PEEIM on the link between swift guanxi and purchase intention among millennial live streaming shoppers in China.

1.9 Significance of the Research

This study on purchase intention among millennial shoppers in live streaming commerce contributes to both theoretical and practical perspectives

1.9.1 Theoretical Significance

This study has theoretical significant in three ways. First, this study has contributed to the existing literature by integrating social factors and technical factors to understand users' purchase intention in live streaming commerce. The socio-technical systems theory provides a useful framework for understanding the factors of socio-technical system success (Chai & Kim, 2012; Hu et al., 2016; Wang et al., 2013). Based on this, this paper puts the theory forward as the underpinning theory of this research and identifies the factors driving the purchase intention of live streaming commerce. Specifically, the theory emphasises that social and technical systems should work together to achieve the best performance of the system (Bostrom & Heinen, 1977). Therefore, the current research argues that the characteristics of streamers are social factors in live streaming commerce, including expertise, attractiveness, authenticity, and interaction orientation, while the technical characteristics are technical factors, including media richness and personalisation, which should be considered jointly to achieve systematic success. Thus, this study extends the socio-technical theory to the live streaming commerce context by emphasising the social and technical factors that determine users' purchase intention.

Secondly, this study adopts the S-O-R model as the supporting theory to comprehend the mechanism of purchase intention in live streaming commerce. The S-O-R model by Mehrabian and Russell (1974) reveals how environmental cues (stimuli) generate a customer's emotional states (organisms) and ultimately lead to customer behavioural outcomes (reactions). In the Chinese online market, business success depends heavily on swift guanxi, which is important for customers to have with sellers as an important mechanism for positive consumer behaviour (Ou, Pavlou, & Davison, 2014). Based on the S-O-R model, this study takes swift guanxi as a mediator of the influence of streamer characteristics and technical characteristics on live streaming commerce purchase intention. In this study, swift guanxi is operationalised as a multidimensional construct consisting of mutual understanding, reciprocal favours, and relationship harmony (Ou, Pavlou, & Davison, 2014).

Finally, this study provides new insights into the live streaming commerce literature by exploring the moderating role of PEEIM on the relationship between swift guanxi purchase intentions using URT (Berger & Calabrses, 1975). Previous research has emphasised the moderating role of PEEIM in the effectiveness of relationship quality (Fang et al., 2014; Q. Huang et al., 2017). However, swift guanxi is different from relationship quality in Western contexts (e.g., trust or satisfaction) (Ou & Davison, 2014). Previous research also called future research to explore whether swift guanxi and PEEIM have a complementary effect in online marketplaces (Chen et al., 2022; Fang et al., 2014). This study therefore empirically explores the moderating role of PEEIM in live streaming commerce and expands the understanding of the factors influencing users' purchasing behaviour.

1.9.2 Practical Significance

Firstly, this study provides valuable insights for sellers and streamers on how to design effective marketing strategies. On the one hand, it offers guidance on the attributes that streamers should emphasise to drive users' purchase intentions. For example, the streamer should be familiar with the product's performance and be able to introduce it clearly to the consumer using in-depth language. Choosing the right makeup and clothes for the streamer's style can enhance their physical attractiveness. Moreover, the streamer should always evaluate the product from the consumer's perspective and actively answer users' questions. The study also emphasises that streamers should focus on forming swift guanxi with users. On the other hand, the study will also help sellers figure out what they should focus on when selecting streamers to endorse their products. For instance, selecting a streamer with strong expertise, such as those with professional qualifications, and uploading the certificates on the platform.

Secondly, competition among different live streaming commerce platforms is fierce. For these platforms, increasing the willingness of massive active users to engage in live streaming shopping is crucial. By emphasising the effectiveness of media richness and personalisation in live streaming commerce platforms, this study provides useful insights for developers. For example, the platform can adopt MR/VR technology to provide a 360-degree full-view immersion, while other senses would be gradually simulated to offer a richer product display. In addition, the platform should improve algorithmic accuracy and serendipity to avoid the 'information cocoon' trap and provide high-quality products and streamers that meet the needs of users.

Lastly, policymakers can use the information from this study to recognise the significant benefits of live streaming commerce to retailers and countries. Therefore, policymakers should provide support, including policy support, live content training, and streamer training, for practitioners to enhance their competitiveness in implementing live streaming commerce.

1.10 Scope of Study

This study focuses on consumers' purchase intention in live streaming commerce. The development of information technology brings a new way for sellers to display and sell products, namely live streaming (Hu & Chaudhry, 2020). Today, most leading e-commerce platforms and social media platforms have incorporated live streaming, giving rise to a new type of social commerce: live streaming commerce (Hu & Chaudhry, 2020). However, the low purchase rate has posed a challenge for streamers and platforms, thus hindering the expansion of live streaming shopping. Moreover, China serves as a significant research context due to its status as a developing country with its broad base of Internet users and dominance in the live streaming commerce industry. Furthermore, despite being a late entrant to the market, live commerce on content-sharing platforms is reshaping the market landscape with its substantial daily active user base and high user stickiness, showing an interesting direction. Douyin, Kuaishou, and Xiaohongshu were selected as the primary setting due to their status as the top three content-sharing live streaming platforms, collectively holding a substantial majority in the content-sharing live streaming market (MOF, 2021). Hence, the main purpose of this study is to explore the determinants affecting Chinese shoppers' live shopping intention on content sharing platforms (Douyin, Kuaishou, and Xiaohongshu).

A quota sampling method was used for this study, and the target population was Chinese millennials (born between 1981 and 1996) who had purchase experience in content live streaming commerce platforms in the past three months. It is expected that studying the behaviour of millennials would yield valuable insights, as this group constitutes the majority of users in the realm of live streaming commerce and possess significant spending power (Chong et al., 2022; Hou et al., 2020; Sharma & Klein, 2020). In general, this study provides scholars and practitioners with valuable insights, especially on how to implement effective strategies to boost users' purchase intention in live streaming commerce.

1.11 Definition of Key Terms

Twelve structures are used in this thesis, which are defined for the current study. All these structures are defined based on popular definitions used by earlier researchers. See Table 1.4 for detailed definitions.

Table 1.4 : Definitions of the Constructs

No	Construct	Definition	Source
1	Expertise	"Accumulated knowledge, skills and competencies that enable a party to be influential within certain domains."	(Ohanian, 1990)
2	Attractiveness	"The extent to which the salesperson is perceived by the customer as possessing an appealing and pleasing physical appearance"	(Ahearne et al., 1999)
3	Interaction orientation	"The salesperson actively interacts with customer and provides them with assistance to form interpersonal relationships."	(Williams & Spiro, 1985)
4	Media richness	"The communication channel's ability to convey messages with rich information. "	(Lee et al., 2009)
5	Personalisation	"Leverages personalisation technologies to provide the right content in the right format to the right person at the right time."	(Tam & Ho, 2006)
6	Swift guanxi	"Buyer's perception of a swiftly formed interpersonal relationship with a seller, which consists of mutual understanding, reciprocal favours, and relationship harmony. "	(Ou, Pavlou, & Davison, 2014)
7	Mutual understanding	"Buyers' and sellers' appreciation of each other's needs."	(Ou, Pavlou, & Davison, 2014)
8	Reciprocal favours	"Positive benefits from buyers' and sellers' interactions."	(Ou, Pavlou, & Davison, 2014)
9	Relationship harmony	"Mutual respect and conflict avoidance."	(Ou, Pavlou, & Davison, 2014)
11	Purchase Intention	"The customer's intention to purchase products or service from sellers via live streaming shopping."	(Sun et al., 2019)
12	Perceived Effectiveness of e-commerce Institutional Mechanisms (PEEIM)	"A buyers' overall perception that the protective institutional mechanisms in e-commerce, such as credit card guarantees, escrow services and privacy protections, can assure the safety and success of transactions."	(Fang et al., 2014)

1.12 Organisation of the Thesis

This thesis is structured into six chapters. Chapter 1 discusses background information on the research topic, followed by the problem statement, research questions, research objectives, the scope of the study, and its significance. Chapter 2 presents a review of the literature related to the theories and constructs used in this research. Chapter 3 outlines the research framework and hypothesis development. Chapter 4 details the research methodology, including the research design, population, sample, survey instrument, and data analysis. Chapter 5 presents the data analysis and results, while Chapter 6 discusses the findings, implications, limitations, and suggestions for future research.

1.13 Chapter Summary

Overall, this study aimed to identify the factors that influence millennial shoppers' live streaming shopping intention on content-sharing platforms in China. This chapter presented the background of the study, discussed the problem statement, the research questions, the research objectives, and the significance of this study. It also outlined the scope and organisation of the study as well as the main constructs. The subsequent chapter delves into the literature review for this study.

CHAPTER 2

LITERATURE REVIEW

2.1 Chapter Overview

First, this chapter discusses the characteristics and behaviours of the target sample, which are millennials. It then reviews the relevant theories applied in previous studies on behavioural intentions in the context of live streaming commerce. This is followed by reviews of previous studies on streamer attributes, technical attributes, and swift guanxi. Moreover, boundary factors that impact consumer behaviour are also presented. Finally, the research gaps in live streaming commerce are discussed.

2.2 The Characteristics and Behaviours of Millennials

The Generation Cohort Theory (GCT) suggests that people of similar ages have similar formative and cultural experiences and exhibit similar values, consumption patterns, and preferences in their consumer behaviour (Ladhari et al., 2019; Purani et al., 2019). This approach has been recognised as an effective segmentation tool, surpassing traditional demographic variables like age and gender (Eastman & Liu, 2012; Parment, 2013). Most previous studies agree to identify up to four groups since 1925: the Silent Generation (born between 1922 and 1945), Baby Boomers (born between 1946 and 1964), Generation X (born between 1965 and 1980), Generation Y or Millennials (born between 1981 and 1996) and Generation Z (born after 1996) (Brosdahl & Carpenter, 2011; Purani et al., 2019).

Millennials will be leading spenders in the next few years. Millennials represent approximately 31.5% of the world's population and nearly 23% of China's population

(China National Bureau of Statistics, 2022). Meanwhile, this cohort has significant disposable income. In 2020, millennials collectively spent \$1.4 trillion, and their combined annual income worldwide is projected to surpass \$4 trillion by 2030 (Khoros, 2020). Furthermore, millennials' lifestyles and behaviours are heavily influenced by the rapid development of technology due to their early access to technology (McCormick, 2016; Purani et al., 2019).

Marketing practitioners and scholars have sought to understand the unique attitudes and behavioural characteristics of millennials. Previous research has shown that, as digital natives, digital technology influences millennials' socializing, hobbies, and shopping (Purani et al., 2019). Compared to previous generations, millennials are very familiar with technology and devices, process information on websites much faster, and tend to engage more in online activities, including online shopping (Bolton & Hoefnagels, 2013; Parment, 2013). They are more willing to engage with brands and retailers through social media (Valentine & Powers, 2013). Social media research further suggests that millennials are twice as influenced by celebrities as Generation X and four times as much as Baby Boomers (Bolton & Hoefnagels, 2013). In addition, the influencer is also considered crucial for millennials' purchase intention (Johnstone & Lindh, 2022) as they see the influencer as someone similar to themselves (Johnstone & Lindh, 2022; Mangold & Smith, 2012). However, despite their particular adaptation to technological innovation, they exhibit more scepticism compared to older generations and feel worried and distrustful of the business activities around them (Ladhari et al., 2019).

Millennials are categorised as more self-centred, more willing to consume, and less likely to be loyal. Designs that meet their utilitarian and hedonic needs would win their trust and business (Bilgihan, 2016). In addition, they seek products or services that resonate with their values (Soares et al., 2017). Therefore, customised products and personalised services have become a new strategy for this specific segment (Ansari & Mela, 2003; Prasad et al., 2019).

As the largest (Bolton & Hoefnagels, 2013), most influential (Ladhari et al., 2019), and fashion-savvy consumer group (Johnstone & Lindh, 2022), millennials represent an essential segment that cannot be ignored. Therefore, considering the large population of Chinese millennials and their growing influence on live streaming commerce, research is needed to comprehend the factors that impact their willingness to purchase and provide helpful information for practitioners to create a successful online business model (Gao et al., 2023; Wang et al., 2023; Zhang et al., 2023).

2.3 Theory in Prior Live Streaming Studies

Behavioural intention refers to people's willingness to try, engage in, and perform a behaviour (Ajzen, 1991). In this study, purchase intention is considered as behavioural intention. It serves as cognitive precursors that predict actual behaviour and have long been recognised as strong predictors of actual purchase behaviours in the live streaming commerce context (Chen et al., 2022).

To gain a comprehensive understanding of existing scholarly works on theoretical frameworks employed to investigate behavioural intentions within the realm of live streaming commerce, a literature review was conducted. The findings of the review are presented in Table 2.1. The findings from the systematic review indicate that a variety of theories have been utilised to examine diverse behavioural intentions within the context of live streaming commerce. Among these theories, the most frequently employed to study behavioural intentions include the Technology Acceptance Model (TAM), Source Credibility Theory, Elaboration Likelihood Model (ELM), and the S-O-R Model. Meanwhile, two studies use the socio-technical theory to understand consumers' post-purchase behaviour. A brief explanation of each theory is presented below.

Table 2.1 : Theories Employed for the Investigation of Behavioural Intentions in the Context of Live Streaming Commerce Research

Theory	Antecedents	Outcomes	Author(s) (year)	Methodology
TAM	Hedonic motivations; utilitarian motivations	Use intention	Cai et al. (2018)	Quantitative (survey)
	Perceived ease of use, perceived usefulness; perceived enjoyment; satisfaction	Payment intention	Sun & Zhang (2021)	Quantitative (survey)
	Ease of use of living stream; usefulness of living stream; affective trust and cognitive trust	Purchase intention	Xie et al.(2023)	Quantitative (survey)
	Source characteristics; perceived ease of use, perceived usefulness; satisfaction; perceived enjoyment	Use intention	Pan et al. (2023)	Quantitative (survey)
IT Affordance theory	Visibility; meta voicing; guidance shopping	Purchase intention	Sun et al.(2019)	Quantitative (survey)
Source credibility theory;	Wanghong-product fit; live content-product fit; Wanghong trustworthiness; attractiveness; attitude; self-product fit	Intention to buy	Park & Lin (2020)	Quantitative (survey)
	Credibility, professionalism, interactivity and attractiveness	Word-of-mouth reputation	Wang et al.(2021)	Mixed(survey)
	Credibility; celebrity effect, perceived entertainment, trust and perceived usefulness	Urge to buy impulsively	Yan et al.(2022)	Quantitative (survey)
	Beauty, expertise, warmth, humour, and passion; hedonic value; utilitarian value	Watching intention; purchase intention; popularity	Guo et all.(2022)	Quantitative (survey)
	Attractiveness; expertise; trustworthiness	purchase intention	Rungruangjit (2022)	Quantitative (survey)
	Expertise, attractiveness, credibility, interactivity, popularity, price support, affinity, and responsiveness		Zhang et al.(2022)	Qualitive (interview)
Elaboration likelihood model (ELM); Source credibility theory;	Bullet screen sentiment; source credibility	Purchase intention	Zeng et al. (2022)	Quantitative (big data set)

Table 2.1 : Continued

S-O-R	Utilitarian value; social value; symbolic value; trust in the product; trust in the seller	Engagement	Wongkitrungrueng & Assarut (2020)	Quantitative (survey)
	Relational bonds; Commitment	Customer Engagement	Hu & Chaudhry (2020)	Quantitative (survey)
	Responsiveness; personalisation; tie strength	Consumer engagement behaviour	Kang et al. (2021)	Quantitative (text mining)
Socio-technical system theory	Interaction; identification; synchronicity; vicarious expression	Stickiness	Li et al. (2021)	Quantitative (survey)
	Active control, two-way communication, synchronicity; visibility, personalisation	Continuance intention	Zhang et al. (2022)	Quantitative (survey)

2.3.1 Technology Acceptance Model (TAM)

TAM was initiated by Davis (1986) based on the Theory of Reasoned Action (TRA) and by incorporating the expectancy confirmation theory and self-efficacy theory, aiming to predict and explain people's acceptance and use of information technology (Venkatesh et al., 2003). TAM highlights two primary constructs, namely perceived usefulness and perceived ease of use (Davis, 1989), which together determine attitudes toward the use of a particular technology, and attitudes further predict the willingness to use (Tarhini et al., 2015). Specifically, perceived usefulness is the extent to which using a particular technology will improve job performance, while ease of use indicates the extent to which using a particular technology is effortless (see Figure 2.1).

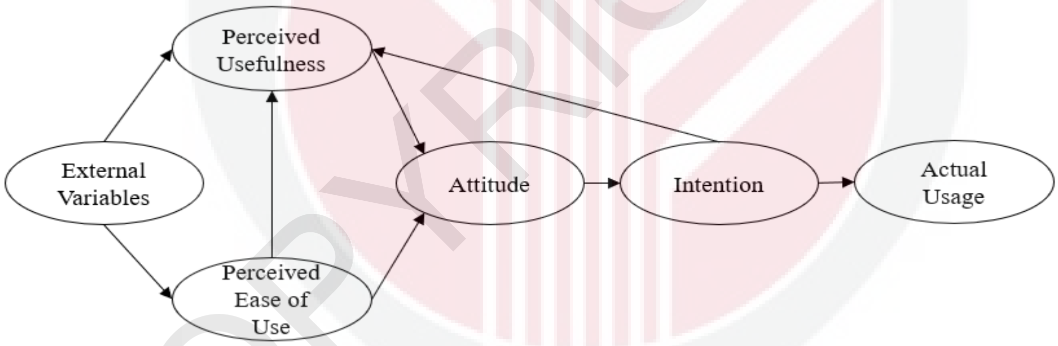

Figure 2.1 : The Original TAM Model
(Source: Davis, 1986)

Davis (1989) subsequently confirmed that attitudes do not fully mediate the effects of usefulness and ease of use on behavioural intentions, as attitudes only represent an individual’s emotions about a particular technology. For example, users may receive pressure from superiors to use certain technology in the enterprise, while their own attitudes toward the technology may be negative. Therefore, by removing attitudes, the TAM model is reconstructed (Davis, 1989; Shih, 2004).

In recent years, TAM's applicability in varying contexts has been widely validated by researchers, for example, in T-commerce (Yu et al., 2005), social media use (Rauniar et al., 2014), mobile commerce (McLean & Wilson, 2019) and online advertising (Lin & Kim, 2016). Additionally, TAM has also been used to explain the consumers' purchase intention and use intention in the context of social commerce (Gibreel et al., 2018; Qing & Jin, 2022) and live streaming commerce (Bründl et al., 2017; Sun & Zhang, 2021).

Although TAM is considered a well-structured model, it also has limitations in explanatory power (Bhattacherjee & Premkumar, 2004; Tarhini et al., 2015). First, TAM emphasises the importance of technology, yet it overlooks the social aspects inherent in the process of technology use (Riffai et al., 2012). TAM may not fully understand the user's intention, particularly in the environment of live streaming commerce, where information is provided by the streamers (Ayeh, 2015). Second, due to its parsimony, TAM has potential inaccuracies in interpreting adoption outcomes, as well as an inability to accommodate unique contextual factors such as privacy, security, and personalisation (Lim, 2018). Finally, TAM is only valid for understanding how consumer intentions are formed when technology use is assumed to be voluntary without any constraints (McMaster & Wastell, 2005; Slade et al., 2015); however, it ignores the persuasive process of technology. On the other hand, the ELM introduced by Hovland Weiss (1951) is an alternate approach taken by researchers in examining behavioural intentions in the context of live streaming commerce.

2.3.2 Elaboration Likelihood Model (ELM)

Cacioppo and Petty (1986) developed the ELM to explain how individuals' attitudes and behavioural intentions can be influenced through two distinct channels of information processing. ELM is regarded as a key, albeit contentious, theory in management (Barta et al., 2023; Gao et al., 2021). It distinguishes between two routes: the central route, which prioritises the quality of arguments, and the peripheral route, which relies on heuristic cues such as source credibility and spokesperson likability (Shiau et al., 2022; Zeng et al., 2022). The central route demands greater cognitive effort and tends to produce more stable attitudes (Petty & Cacioppo, 1986). ELM also describes a continuum of elaboration that ranges from shallow to deep processing. Factors like motivation and involvement determine whether individuals engage with the central or peripheral route when assessing persuasive messages (Gao et al., 2021; Petty & Cacioppo, 1986). This means that the same information can have varying effects on different individuals (Shiau et al., 2022) (see Figure 2.2).

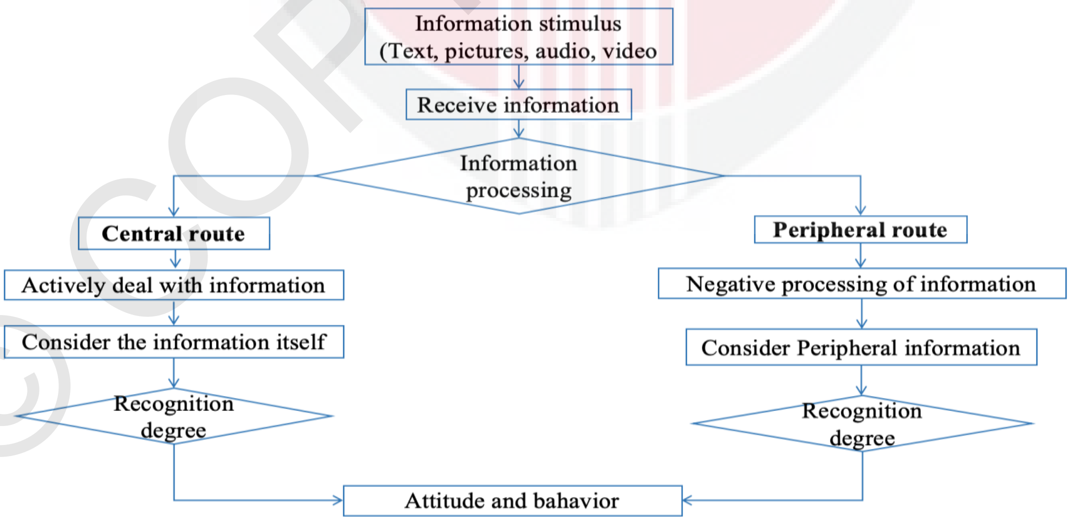

Figure 2.2 : Elaboration Likelihood Model
(Source: Cacioppo & Petty, 1986)

ELM has been applied across diverse fields, including social psychology (Gu et al., 2017; Wang et al., 2019), health (Chen et al., 2018), education (Zhang et al., 2021), and social media (Barta et al., 2023). Additionally, ELM is essential for understanding consumer behaviour amid complex messages in the context of e-commerce (Shiau et al., 2022) and live streaming commerce (Gao et al., 2021; Zeng et al., 2022).

Like other theories, ELM has faced some criticism. Firstly, it can be challenging to differentiate between central and peripheral routes due to the need to consider potential similarities in persuasive outcomes during information processing (Bhattacherjee & Sanford, 2006). Secondly, the ELM model overlooks the possibility of intermediate mechanisms within an individual's information processing pathway (Shiau et al., 2022). The source credibility theory, developed by Hovland Weiss (1951), offers a different perspective for researchers exploring behavioural intentions within the realm of live streaming commerce.

2.3.3 Source Credibility Theory

The source credibility theory was originally proposed by psychologist Hovland to understand the effectiveness of communication (Hovland & Weiss, 1951). According to this theory, the validity of a message is determined by the expertise and trustworthiness of the source. Expertise is defined as the degree to which the audience perceives the communicator as a source of valid assertions, while trustworthiness pertains to the communicator's confidence in the source to provide information objectively and honestly (Hovland & Weiss, 1951). Ohanian et al. (1990) expanded the concept of source credibility into the realm of celebrity endorsements, defining it as any positive trait of the source communicator that influences the receiver. They suggested that sources credibility for advertising celebrities encompass expertise, attractiveness, and trustworthiness (Ohanian et al.,1990) (refer to Figure 2.3). In recent years, source credibility has been expanded into different combinations, including dynamism (GIFFIN, 1967), homophily (Ladhari et al., 2020), interactivity (Ryu & Han, 2021), and popularity (Ki & Kim, 2019).

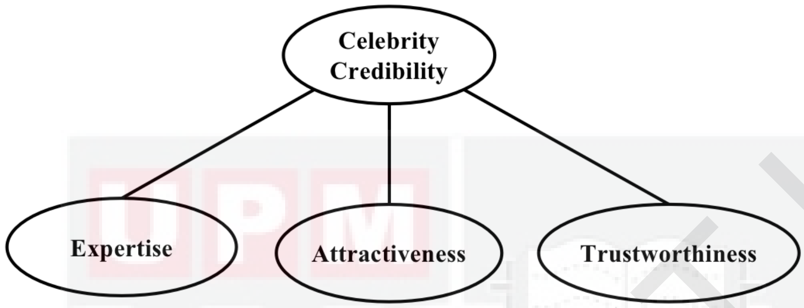

Figure 2.3 : The Original Source Credibility Model
(Source: Ohanian, 1990)

Source credibility has received extensive attention in marketing and communication literature, including celebrity endorsements (Amos et al., 2015; Calvo-Porral et al., 2021), electronic word of mouth (eWOM) usage (Hussain et al., 2017; Ismagilova et al., 2020), and influencer marketing (Sokolova & Kefi, 2022; Wiedmann & von Mettenheim, 2020). For example, Ismagilova et al. (2020) conducted a meta-analysis of electronic eWOM communications and found that the characteristics of source credibility are significantly related to eWOM usefulness and credibility, intention to purchase, and information adoption. Similarly, Li and Peng (2021) employed the source credibility perspective in examining consumers' positive attitudes and subsequent purchase intention in influencer marketing, whereas Kim and Kim (2021) investigated the influence of source characteristics on winning loyalty customers.

Although the source credibility theory provides a valuable framework for understanding the relationship between the different characteristics of a message's source and message validity, its limitations need to be considered when applying it. First, the characteristics of the sources that users focus on vary across contexts, which has prompted scholars to explore the different dimensions of source credibility in each context (GIFFIN, 1967; Li & Peng, 2021; Ohanian, 1990). In addition, the use of source credibility theories in isolation may overlook the important impact of technology, especially on online platforms where the technical characteristics of the medium are closely related to credibility assessment (Liao & Mak, 2019). Therefore, scholars have called for other theories and approaches to achieve a more comprehensive understanding (Ayeh, 2015). In this situation, the socio-technical theory proposed by Trist et al. (1963) is another approach used by researchers in studying behavioural intentions.

2.3.4 Socio-Technical Theory

The socio-technical theory was originally proposed by Trist et al. (1963) to study organisational optimisation. By examining the formation of autonomous miners, Trist et al. (1963) argued that any productive organisation is a socio-technical system formed by the interaction of the social and technical subsystems (Trist et al., 1963). This theory rejects the idea that technology is the primary determinant of organisational outcomes, and that people are dispensable. Instead, it views individual as a "resource to be exploited" rather than dispensable people, and contends that economic optimisation can only be achieved through a combination of social and technological systems (Trist et al., 1963). In the socio-technical theory, the technical subsystem emphasises the process, tools, and technology that users can use to convert input into output to complete system tasks. In contrast, the social subsystem emphasises human knowledge, values, attitudes, and skills (Bostrom & Heinen, 1977) (see Figure 2.4).

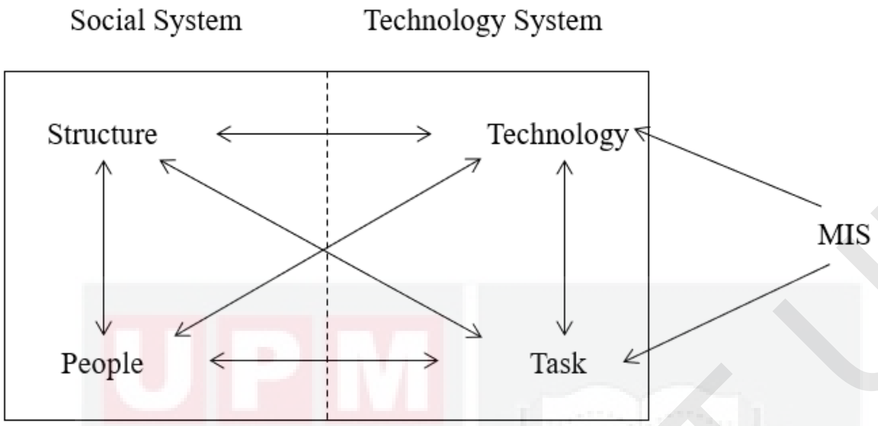

Figure 2.4 : Socio-Technical System Theory
(Source: Bostrom & Heinen, 1977)

The socio-technical theory has been applied to a wide range of disciplines, particularly organisational systems (Eijnatten, 1998; Morison & Hughes, 1991; Mumford, 2006) and security management and engineering (Andersson et al., 2019; Evers et al., 2016; Jean-Jules & Vicente, 2021), using both qualitative and quantitative methods as well as socio-technical design approaches. Moreover, the socio-technical theory has been applied at multiple levels, from micro to macro. It can be applied to work systems within organisations, entire organisations, and up to macro-social systems at the social level, such as the industrial sector (Trist, 1981). This approach traditionally focuses on the work system or organisational or sectoral level to achieve optimisation of economic, work-related, and other outcomes (Trist, 1981).

The socio-technical theory also gained attention from scholars in information system research. It has been used to evaluate the effectiveness of online information technology (see Table 2.2) (Chai & Kim, 2012; Gibreel et al., 2018; Hu et al., 2016;

Kong et al., 2020; Krotov, 2015; Lee, 2018; Tajvidi et al., 2020). In other words, it has been employed to identify the critical role of the combination of digital technologies and social factors that lead to positive outcomes, such as user engagement, purchase intention, and continued use intention (Chai & Kim, 2012; Hu et al., 2016; Kong et al., 2020). Social factors in this context are people-related, including human characteristics (Hu et al., 2016), identification (Wan et al., 2017) and interaction (Wan et al., 2017), while technical factors are related to the unique technology of information system, encompassing convenience (Wang et al., 2013), personalisation (Wan et al., 2017), and information quality (Kong et al., 2020). Previous research has further argued that the improvement of social factors and technical factors alone could not bring about the success of the information system, and the interaction effect of the two subsystems must be considered in order to achieve optimal system performance (Bostrom & Heinen, 1977; Wan et al., 2017).

Early research by Lin et al. (2008) on virtual communities showed that technical features and social factors are critical for implementing thriving communities. This view is supported by Chen and Qi (2015), who found that technical factors represent the usefulness and ease of use of the system. In contrast, social factors include social interaction ties, trust, reciprocity, and shared vision. Social and technical factors together increase user satisfaction and willingness to continue using. A study conducted by Wan et al. (2017) suggested that social factors and technical factors are the main drivers that influence users' donations to content creators. Specifically, increasing technical features promotes users' functional dependence on the platform. Similarly, as a favourable feature, social factors increase users' attachment to content creators. Dependence on platform functionality and dependence on content creators jointly increase users' donation intention. The socio-technical theory has also been used as a theoretical basis to understand the factors that stimulate purchase intention in social commerce (Hu et al., 2016). The findings show that peer expertise, similarity, and benevolence were social factors that drove social commerce purchase intention, while support for social interaction and support for recommendation were technological factors that encourage purchase intention (Hu et al., 2016).

Table 2.2 : Previous Studies on Socio-Technical Theory

Author, Year	Social	Technical	Mediator	Context
Wang et al. (2013)	Network size, Existing social contacts	Interactivity, Convenience, Accessibility	performance expectation, sense of belonging, hedonic expectation	User Acceptance of Micro-Blog Services
Shareef (2013)	Behavioural attitude, Cognitive perception	Perceived security, Perceived privacy, Fulfilment	/n	Purchase behaviour
Hu et al. (2016)	Peer characteristics: Similarity, Expertise, Benevolence;	Support for social interactions, Support for recommendations	Perceived value	Purchase intention in social commerce
Wan et al. (2017)	Identification, Interaction, Information value	Sociability, Personalisation	Attachment	Willingness to donate to content creators in social media
Gibreel et al. (2018)	trust and familiarity	Governing form factor and technological utility	perceived ease of use, Trust, perceived usefulness	Adoption Intention of social commerce
Al-Adwan (2019)	Familiarity, User experience	Social commerce constructs	Trust, PU, PEU	Purchase intention and actual purchase in social commerce
Maurya & Gayakwad (2020)	Familiarity, Learning and training, User experience	Social commerce constructs	PU, PEU, trust	Intention to buy
Tajvidi et al. (2020)	social support, Relationship quality	Information sharing, Forums and communities, Ratings and reviews	social support	Brand co-creation
Kong et al. (2020)	Social referrals	Information quality, Transaction Safety	Trust	Continuance use of Airbnb/eWOM

In summary, the socio-technical system theory provides a valuable and holistic framework for understanding consumer behaviour (Chen & Qi, 2015). It enables researchers to capture social and technical factors to understand individual behaviour in online information systems, including mobile learning (Krotov, 2015), social media (Chai & Kim, 2012; J. Lee, 2018), sharing commerce (Kong et al., 2020; Tajvidi et al., 2020), and social commerce (Gibreel et al., 2018; Hu et al., 2016). In addition to this theory, some studies have also used the S-O-R model to understand the mechanisms driving an individual's purchase intention. The S-O-R model is discussed in detail in the next section.

2.3.5 S-O-R Model

The S-O-R model, first proposed by environmental psychologists Mehrabian and Russell (1974), was developed to understand how individuals respond to the physical environment. This model is an extension of the S-R theory (Moore, 1996). Initially, the S-R paradigm was proposed by a large number of experimental psychologists to comprehend how animals learn (Lee et al., 2016; White, 1993). Laboratory experiments by these psychologists demonstrated that in the S-R theory, the learning ability of animals evolves in response to different external stimuli. However, this theory has been heavily criticised since it does not consider the components of an individual's internal states (Moore, 1996; White, 1993). To explain cognitive and affective processes within the organism, Woodworth (1929) introduced mediating variables between stimulus and response and proposed the S-O-R process based on the traditional stimulus-response theory. Woodworth (1929) explained that these mediating variables could be motivation, purpose, or the tendency to respond to a stimulus.

Mehrabian and Russell (1974) further proposed a paradigm based on this S-O-R process to expand the theory that environmental cues (S) can impact an individual's cognitive and emotional reactions (O), which in turn affect their behaviour (R) (see Figure 2.5). Specifically, the S-O-R model consists of three components: (1) the stimulus (S) indicates the physical (e.g., atmosphere and layout) and social cues (e.g., employees' emotions and interactions) in the external environment (Eroglu et al., 2003; Hu et al., 2016); (2) the organism represents the individual's internal state or organic response to S; it mediates the relationship between the stimulus and the final action. Eroglu et al. (2003) mentioned that the organism refers to "the internal processes and structures located between the person's external stimuli and the final action, reaction, or response, consisting of perceptual, mental, sensory, and thinking activities" (p. 46). In this stage, individuals transform stimuli into meaningful information based on their emotional state, which is then used to interpret the environment prior to planning (Peng & Kim, 2014); and (3) reaction is the behavioural response to O (i.e., approach versus avoidance).

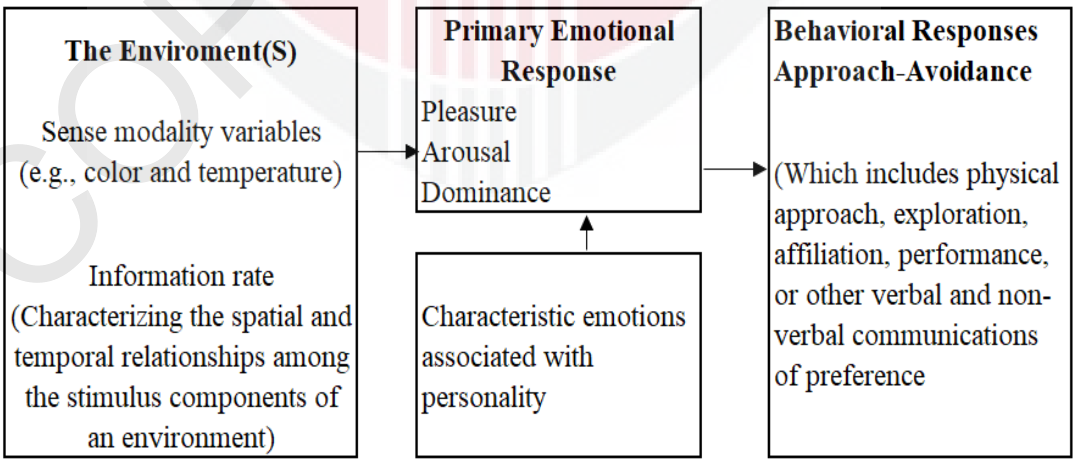

Figure 2.5 : S-O-R Model
(Source: Mehrabian & Russell, 1974)

The S-O-R model is one of the fundamental theories of online buying and forms the basis of consumer behaviour research (Kimiagari & Asadi Malafe, 2021) (see Figure 2.6). For example, Liu et al. (2016) investigated how online interpersonal factors affect the purchase intentions of social commerce consumers across age groups. Similarly, a study conducted by Li (2019) investigated the impact of social commerce constructs as a stimuli on purchase intention. Likewise, social support and subjective norms were identified as drivers of trust, which in turn promote purchase intention among social commerce users (Liu et al., 2019).

A review of previous studies revealed that the S-O-R model is beneficial for three reasons. First, the S-O-R model is a fundamental theory that can be linked to other theories to present an interdisciplinary model by incorporating multiple stimuli and organisms (Hu et al., 2016; Lin et al., 2017; Mehrabian & Russell, 1974). Secondly, the S-O-R model enables researchers to identify the unique elements of an online platform and construct a comprehensive model that reflects how user interaction with this artifact results in good consumer behaviour (Hu et al., 2016; Lin et al., 2017). Lastly, previous studies have consistently validated the applicability of the S-O-R model for online consumer behaviour research (Hu et al., 2016; Lin et al., 2017).

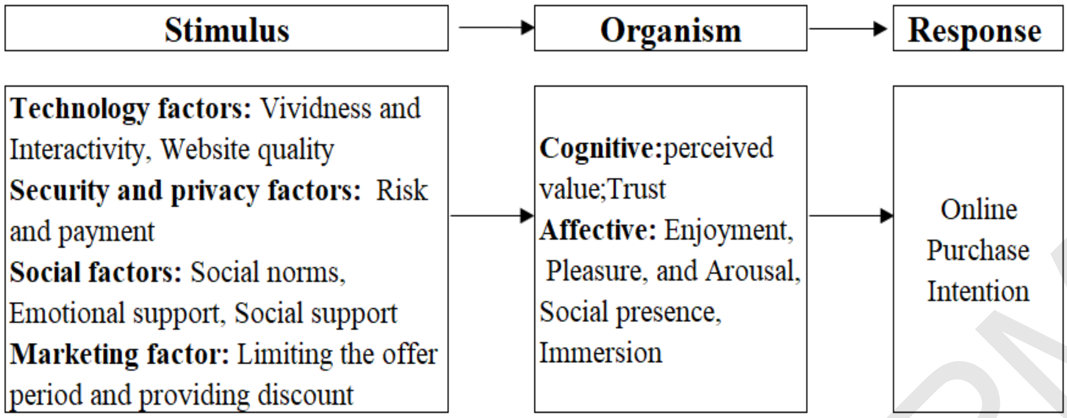

Figure 2.6 : The S-O-R Model of Consumer Behaviour in the Online Shopping Environment in Recent Years
(Source: Hu et al., 2016; Lin et al., 2017; Mehrabian & Russell, 1974)

2.3.6 Final Remarks of Theories in Live Streaming Studies

Nowadays, live streaming commerce has become a trend in e-commerce. Based on the well-established TAM and source credibility theory, authors of previous studies have focused on either technical or social aspects of live streaming services (Chong et al., 2022; Oyedele & Simpson, 2018; Singh et al., 2021). These studies investigate the constructs such as perceived ease of use, perceived usefulness, and behavioural intention (e.g., Bründl et al., 2017; Sun & Zhang, 2021; Zhou et al., 2021). However, these theoretical models have received a great deal of criticism. It does not consider both the social factors and technical factors in the system (Riffai et al., 2012). In the environment of live streaming commerce particularly, where both the streamer and technology are key elements that cannot be ignored, TAM and the source credibility theory may not provide a comprehensive understanding of consumer behaviour (Ayeh, 2015).

Accordingly, the socio-technical theory of Trist (1963) has received considerable attention in the context of behavioural intention. According to this theory, the successful implementation of a technological system needs to consider both social and technological factors. Compared with other theories, the socio-technical theory provides a more structured theoretical framework to develop an integrated model for the complexity of user behaviour. The theory shows wide applicability in a variety of technical environments, such as T-commerce (Yu et al., 2005), social media (Rauniar et al., 2014), social commerce (Gibreel et al., 2018; Qing & Jin, 2022) to determine users' technology usage behaviour. Therefore, this is a more suitable theoretical basis for studying the use of live streaming commerce. This study extends this theory by integrating the S-O-R model to understand the intervention process between input and output. As highlighted in previous work, the S-O-R model is used as a theoretical basis to understand how environmental stimuli affect consumer feelings (Kim et al., 2020; Lin et al., 2017) and behavioural intention (Hsu & Tsou, 2011; Xue et al., 2020).

In conclusion, the socio-technical theory provides a more comprehensive basis for examining the underlying factors driving the purchase intention of live streaming commerce. It allows researchers to identify social factors as well as technical factors in the context of e-commerce live streaming. In practice, this theoretical perspective provides useful insights for practitioners to understand the salient features that consumers need when using live streaming commerce. In addition, in the case of live streaming commerce, this study proposed streamer attributes (expertise, attractiveness, interaction orientation) as social factors and technical attributes (media richness, personalisation) as technical factors, respectively. Specifically, this study believes that the positive characteristics of both the streamer and the technical aspects must be jointly optimised to maximise the success of live streaming commerce.

2.4 Underpinning Theory: Socio-Technical Theory

The socio-technical theory proposed by Trist (1963) has been utilised to comprehend users' online participation and purchasing behaviour. Technical subsystems encompass processes, tools, and techniques that enable users to transform inputs into outputs and complete specific tasks within the system, while social subsystems comprise users, knowledge, values, relationships, and reward systems. These subsystems must work in concert to achieve optimised outcomes.

The socio-technical theory has been used to investigate knowledge sharing on social media platforms (Chai & Kim, 2012; Lee, 2018), sharing commerce (Kong et al., 2020; Tajvidi et al., 2020) and m-learning (Krotov, 2015). Nonetheless, this theory has not been widely applied to the field of live streaming commerce. Therefore, this study extends the socio-technical theory to live streaming commerce for two reasons. First, this theory offers a more appropriate and structured framework for identifying key factors that influence user behaviour (Hu et al., 2016; Zhang et al., 2019). Second, with the proliferation of live streaming platforms and streamers, scholars are increasingly called upon to adopt a more integrated set of factors to examine users' purchase intention. As argued by Ma (2021a), both social and technical factors should be integrated to achieve optimal performance of live streaming commerce. Based on these arguments, Trist's (1963) socio-technical theory supports this study's assertion that streamer attributes and technical attributes are two significant drivers of purchase intention in live streaming commerce. Specifically, streamer attributes represent social factors, while technical attributes represent technical factors that add value to live streaming commerce.

2.5 Support Theories

This study employs the S-O-R model and uncertainty reduction theory as the theoretical basis for introducing the mediator (i.e., swift guanxi) and moderator (i.e., PEEIM). They are explained in the following subsections.

2.5.1 S-O-R Model

The S-O-R model, developed by Mehrabian and Russell (1974), stands as one of the most influential models for explaining the effects of the physical environment on human behaviour (Lin et al., 2017). The model suggests that cues (stimuli) perceived from the environment can motivate an individual's internal state (organism), resulting in positive or negative behaviour (response) to the stimulus (Mehrabian & Russell, 1974).

In recent years, this model has been widely used in the online marketplace to illustrate how characteristics of the online store environment affect consumers' decision-making processes (Bedi et al., 2017). The literature review suggests that online environmental cues, encompassing technological factors, social factors, marketing stimuli, and security privacy, serve as stimuli that broadly impact users' internal states, such as cognition and emotions, consequently leading to positive behaviours.

The S-O-R model emphasises the organism as the primary link between stimulus and response, aligning well with the use of relationship management to enhance positive consumer responses. Consistent with Ou et al. (2014), this study asserts that swift guanxi is a crucial mechanism for eliciting positive consumer behaviours in online commerce. Recognising the critical role of relationship marketing, recent studies have also highlighted the increasing importance of the quality of the firm-consumer relationship (Palmatier et al., 2006; Verma et al., 2016). Therefore, this study considers social and technical attributes as external stimuli, swift guanxi as the organism, and purchase intention as the response. Additionally, social factors were categorised into the expertise, attractiveness, and interaction orientation of streamers, while technical factors were classified as media richness and personalisation. This categorisation enables researchers and practitioners to evaluate the relative significance of each streamer attribute and technical attribute in fostering swift guanxi and purchase intention (Tseng et al., 2022).

2.5.2 Uncertainty Reduction Theory (URT)

The uncertainty brought by the online environment is the primary reason consumers are unwilling to make purchases. In online commerce, perceived uncertainty refers to the extent to which buyers are unable to accurately predict the result of a transaction owing to uncertainty regarding the seller, product, transaction process, or system-dependent uncertainty (Grabner-Kraeuter, 2002). URT indicates that the unpredictability of outcomes prompts both parties to employ strategies to reduce uncertainty (Berger & Calabrses, 1975).

In this study, PEEIM is considered as an uncertainty reduction strategy, which can mitigate users' perception of uncertainty in live streaming commerce environments, such as privacy concerns and transaction processes. In secure settings, users are more likely to demonstrate favourable behaviours (Chen et al., 2015). Conversely, if PEEIM is low, although swift guanxi can reduce users' uncertainty regarding sellers and products, uncertainty regarding the transaction process and privacy diminish users' willingness to make purchases.

2.6 Streamer Attributes

Streamers refer to a new type of salesperson that provides consumers with product demonstrations, trials, and usage experiences on live streaming platforms, thereby encouraging consumers to make purchases (Hu & Chaudhry, 2020). Live streaming can show the streamer's faces, expressions, personalities, and real-time interactions with the products (Guo et al., 2022; Wongkitrungrueng et al., 2020), which will bring the offline salesperson's selling skills online. Unlike traditional online shopping, streamers act as online shopping guides, thoroughly explaining product details. They visually display the functions of the product, which makes up for the disadvantages of incomplete information brought by static webpages (Wongkitrungrueng et al., 2020). Prior literature on offline marketing suggests that salesperson attributes are a key social factor influencing consumer behaviour (Babin et al., 1999; Palmatier et al., 2006). A similar situation may occur in live streaming commerce. Thus, streamers attributes are regarded as critical social factors in the context of live streaming commerce.

Source credibility is widely used to understand communicator attributes. The model suggests that the receiver's perception of the communicator's credibility has a critical impact on the persuasiveness of the communicated message. Based on an extensive literature review, source credibility has been described as having different but overlapping dimensions. Source credibility (Hovland et al., 1953) incorporates expertness and trustworthiness to understand source credibility by analysing the factors that contribute to communicator credibility. Berlo et al. (1969) further extended Hovland's source credibility model by arguing that safety, qualification, and dynamism determine source image. Similarly, a study conducted by Giffin (1967) showed that if users perceive a speaker as having expertise, reliability, dynamism, and personal charm, the listener is more likely to form interpersonal trust in the speaker. Dynamism indicates that the listener perceives the speaker's communication behaviour as more active than passive (GIFFIN, 1967).

Ohanian et al. (1990) extended the source credibility model to the field of endorsements and argue that the effectiveness of endorsements depends primarily on the endorser's expertise, attractiveness, and trustworthiness. In recent years, source credibility has been expanded into different combinations, including interactivity (Ryu & Han, 2021) and popularity (Kim & Kim, 2019). Source credibility has also been used in a wide range of areas, including advertising endorsements (Amos et al., 2015; Calvo-Porral et al., 2021), influencer marketing (Sokolova & Kefi, 2022; Wiedmann & von Mettenheim, 2020), and eWOM usage (Hussain et al., 2017; Ismagilova et al., 2020). Overall, prior research has focused on understanding source credibility through expertise, attractiveness, trustworthiness, and dynamism.

Previous studies have widely used the dimension of the source credibility model to understand streamer attributes. As the main content creator, streamers have become key to successful marketing in live streaming commerce. Correspondingly, a few studies have explored the roles of streamers in this context (see Table 2.3). For example, Park and Lin (2020) suggests that streamers' expertise have a positive effect on online product sales. The study of Lee and Chen (2021) holds the same view and further validates that streamer attractiveness, expertise, and trustworthiness are drivers impulsive purchasing. Likewise, a recent study emphasised that the authenticity of the streamer is positively related to relationship formation and positive behavioural intention (Liu & Sun, 2023). All these characteristics are factors that come from source credibility models. In general, streamer characteristics are assessed primarily through the credibility of the streamer in three aspects: attractiveness, expertise, and trustworthiness. Additional streamer characteristics, like likeability, animacy, responsiveness, and coolness have also been suggested as virtual streamer characteristics that influences user behaviour in live streaming commerce (Gao et al., 2023; Wang et al., 2023; Zhang et al., 2023). However, users hold different expectations from human streamers and virtual streamers (Wang et al., 2023); therefore, the characteristics of these virtual streamers are not considered in this study.

Table 2.3 : Literature on ELS Streamer Characteristics

Characteristics	Streamer type	DV	Author, Year
Expertise	Human	Purchase intention; Use intention; Satisfaction; Urge to buy impulsively	Park & Lin, (2020) Ma, (2021) Lee & Chen, (2021) Rungruangjit, (2022) He & Jin, (2022) Pan et al., (2023)
Attractiveness	Human	Purchase intention; Use intention; Satisfaction; Urge to buy impulsively	Park & Lin, (2020) Lee & Chen, (2021) Gao et al., (2021) Rungruangjit, (2022) He & Jin, (2022)
Trustworthiness	Human	Purchase intention; Use intention; Satisfaction; Urge to buy impulsively	Ma, (2021) Gao et al., (2021) Lee & Chen, (2021) Rungruangjit, (2022) He & Jin, (2022)
Host charm;	Human	Purchase intention; Use intention; Satisfaction; Urge to buy impulsively	Wang et al., (2021)

Table 2.3 : Continued

Credibility	Human	Purchase intention; Urge to buy impulsively	Yan et al., (2022) Zeng et al., (2022)
Authenticity	Human	Purchase intention	Liu & Sun, (2023)
Coolness	Virtual	Impulsiveness	Zhang et al., (2023)
Likeability	Virtual	Purchase intention	Gao et al., (2023)
Animacy	Virtual	Purchase intention	Gao et al., (2023)
Responsiveness	Virtual	Purchase intention	Gao et al., (2023)
Predictability	Virtual	Trust; Purchase intention	Wang et al., (2023)

Customers hold conflicting or suspicious attitudes toward the motives of the streamer's behaviour in the early stages (Li & Peng, 2021; Lou & Yuan, 2019). As a result, some consumers may not trust the streamer until there is enough interaction (Li & Peng, 2021; Lou & Yuan, 2019). Thus, this study did not include trustworthiness as the streamer attribute.

In addition, real-time interaction and communication between streamers and users are crucial aspects of live streaming commerce (Kang et al., 2021; Sun et al., 2019). This highlights the importance of streamers' communication strategies for customer retention (Guo et al., 2022; Wongkitrungrueng et al., 2020). While some researchers have examined the influence of perceived interactivity on consumer purchase intentions (Joo & Yang, 2023), there has been limited exploration of the styles of streamer interaction. Previous studies indicate that the interaction-oriented communication style in online reviews is critical for customer information assessment (Fitriani et al., 2020) and can effectively elicit consumer responses (Williams & Spiro, 1985). In the context of live streaming, the combination of interpersonal interactions and shorter durations further emphasises the significance of the streamer's interaction orientation. Effective interactions can capture consumer attention and enhance positive behaviour.

On the other hand, previous reviews of relationship marketing have shown that seller characteristics and relational behaviours (e.g., communication style, interaction frequency, and duration) are essential antecedents of relationship quality (Crosby et al., 1990; Palmatier et al., 2006). However, Kang et al. (2021) reveal that in live streaming commerce, interaction intensity does not always lead to positive user engagement. This aligns with Zhang et al. (2024), who suggest that excessive interaction can cause information overload, resulting in a decline in product sales after a certain point. Consequently, this study does not focus on interaction intensity; it only concentrates on interaction orientation. Based on the above, expertise, attractiveness, and interaction orientation are chosen as the three main attributes of the streamer in this study.

2.6.1 Expertise

Expertise refers to accumulated knowledge, skills, and abilities that enable a party to become influential within certain domains (Mayer et al., 1995). An expert means a person has reached the highest level in the respective field. Becoming an expert requires hard work, practice, experience, and long-term training (Calvo-Porral et al., 2021; Wiedmann & von Mettenheim, 2020). Individuals can identify experts and ordinary people by their knowledge and achievements (Ismagilova et al., 2020). For example, people can perceive higher expertise when the title “Dr.” rather than “Mr.” is used to address a person. de Bont and Schoormans (1995) provide an overview of how expertise guides consumers' information processing. First, spokespeople with expertise have a more detailed cognitive structure about a product. Expertise will improve the spokesperson's knowledge of product details, which means that a professional spokesperson can develop a more detailed concept of the product and a better evaluation of the product (de Bont & Schoormans, 1995). Second, spokespeople with expertise can make in depth analysis. Expertise means that spokespeople have stronger analytical skills and evaluate more attributes in the analysis of the product. In contrast, spokespeople with less expertise rely more on the overall assessment, while the overall evaluation analyses only one or two attributes of the product (e.g., price) (Chaiken & Maheswaran, 1994). Finally, spokespeople with expertise have a greater ability to make functional inferences. Previous studies have shown that the benefits offered by the product, rather than the product's features, were the main motivation for consumers to purchase (Ratchford, 1975). Also, expertise enhances the spokesperson's ability to make functional inferences about the product, thus allowing consumers to better understand the value of the product (de Bont & Schoormans, 1995).

Previous studies have demonstrated that expertise is associated with brand awareness (Wiedmann & von Mettenheim, 2020), the effectiveness of endorsement (Ismagilova et al., 2020; Ladhari et al., 2020; Ohanian, 1991; Wiedmann & von Mettenheim, 2020), eWOM usefulness (Ismagilova et al., 2020; Reichelt et al., 2014) and an individual's popularity (Guo et al., 2022; Ladhari et al., 2020). Empirical studies of celebrity endorsements have shown that the influence of information increases when it comes from experts in a specific field (Lis & Post, 2013). Likewise, in eWOM communication, the information provided by reviewers with expertise was perceived to be more useful than that provided by reviewers with low levels of expertise. Thus, they are more likely to adopt it (Filieri et al., 2018; Ismagilova et al., 2020).

Furthermore, an individual's expertise is also an essential factor in making eWOM messages more convincing and increase users' willingness to purchase (Filieri et al., 2018; Ismagilova et al., 2020). The positive effect of expertise has also been widely demonstrated in the effectiveness of influencer endorsement, where higher expertise influencers can provide more valuable and relevant information and reduce information asymmetry (Liu, 2022).

Previous studies have shown that consumers are more likely to interact with salespersons or peers with expertise (Ma, 2021a). Information provided by expertise can significantly reduce consumers' efforts in product search, evaluation, and decision-making (Hu et al., 2016). Similarly, expertise is considered a key attribute of streamers in live streaming shopping.

2.6.2 Attractiveness

Physical attractiveness indicates the degree to which a salesperson's physical appearance is pleasing (Baker & Churchill, 1977). People who are physically attractive are more likely to be perceived as more prominent in other aspects, and this halo effect responds to stereotypes of physical attractiveness (Baker & Churchill, 1977; Joseph, 1982). For example, people with physical attractiveness are perceived as kind, interesting, strong, and social (Dion et al., 1972). They are also perceived as more logical, decisive, and motivated (Joseph, 1982). Furthermore, physically attractive people are perceived to be more trustworthy and capable than those with plain appearance (Ahearne et al., 1999; Till & Busler, 2000).

The effect of attractiveness has been revealed in various fields. Studies have found that physical attractiveness influences judicial judgment, resulting in decisions being more favourable to attractive litigants (Kulka & Kessler, 1978). Similarly, physical attractiveness also influences employee job searches, with attractive applicants more likely to be favoured by employers (Dipboye et al., 1976). Communicators who are outwardly attractive also show a greater ability to persuade and change the attitude of the other party (Chaiken, 1979).

The effect of attractiveness has also attracted the attention of marketing researchers and has been explored in the areas of personal sales (Peng et al., 2020), celebrity endorsement (Gong & Li, 2017; Till & Busler, 1998) and influencer marketing (Li & Peng, 2021; Wiedmann & von Mettenheim, 2020). Sellers with attractive appearances were perceived to possess greater sociality and competence, consequently enjoying higher credibility and increased sales. This effect is more pronounced for products related to appearance (Peng et al., 2020). In addition, endorsements by attractive celebrities result in more positive perceptions of products and advertising among consumers compared to endorsements by less attractive celebrities (Gong & Li, 2017; Till & Busler, 1998). Similarly, social media influencers also emphasise attractiveness as an important factor in winning followers (Munnukka et al., 2019) and positive purchase intentions (Munnukka et al., 2019; Sokolova & Kefi, 2022), as users are more likely to form a para-social relationship with them. However, previous research suggests that the positive effect of attractiveness is greater in the short term and diminishes over time (Eisend & Langner, 2010).

Due to the visibility of live streaming commerce, the appearance the streamer can be recognised by users (Sun et al., 2019). Considering that attractiveness is an important driver for acquiring and retaining consumers, attractiveness is considered a key attribute of the streamer.

2.6.3 Interaction Orientation

Communication style refers to a person's tendency to communicate using specific patterns or rules (Williams & Spiro, 1985). Sheth (1976) identified three main categories of communication styles: task-oriented, interaction-oriented, and self-oriented. Task orientation is a communication style that focuses on efficiency, being highly goal-oriented and purposeful. Interaction orientation, also known as social orientation or relationship orientation, is a communication style that emphasises socialisation and avoids conflict. Moreover, self-orientation is a self-centred, self-pleasing way of communication. With the support of technology, communication style is not only used offline (Li & Ma, 2022), but also online (Fitriani et al., 2020). In the context of live streaming commerce, interaction orientation means that the streamer/seller actively interacts with and offers help to the audience (Liao et al., 2022).

Communication styles have been used to evaluate the effectiveness of communication in various contexts, including professional service (e.g., health services, financial services, medical consultation, construction, accounting and legal services) (Patterson, 2016; Roongruangsee et al., 2022), non-professional service (Li & Ma, 2022), online intelligent robot or online anthropomorphic assistant (Rafaeli et al., 2017), smart IoT (Wu et al., 2017) and chatbots (Chen et al., 2020). Previous research has shown that when users lack sufficient knowledge and solutions to problems, they judge services based on how the provider or seller communicates or treats them (Chen et al., 2020). Professionals who adopt sociable communication can increase clients' evaluation of service quality and satisfaction. This positive effect can be explained by the uncertainty reduction theory and signalling theory. Service providers employing a sociable communication style typically create positive impressions, alleviate client uncertainty and anxiety, and enhance user comfort, satisfaction, and willingness to pay (Patterson, 2016; Roongruangsee et al., 2022). In a non-professional service context, an interaction-oriented communication style allows the customer to take uninterrupted ownership and control of the service process, thus gaining perceived control and comfort (Li & Ma, 2022).

Interaction-oriented communication styles focus on cultivating good interpersonal relationships (Fitriani et al., 2020). Directly communicating and interacting with audiences on social media is conducive to forming the interpersonal relationship between communicator and audiences (Corrêa et al., 2020; Phua & Ahn, 2016). Salespeople using an interaction-oriented communication style can exhibit their warmth, friendliness, and approachability through verbal and non-verbal behaviours, thereby enhancing physical and mental intimacy (Darian et al., 2005). Furthermore, customers who feel cared for feel comfortable and valued, leading to more contact with sellers (Patterson, 2016). This exposure produces positive effects, including purchase intention, recommendation intentions, loyalty, and other positive outcomes. Moreover, previous studies have analysed interaction orientation communication in the smart device. For example, Keeling et al.'s (2010) research shows that avatars' interaction orientation communication with users in retail helps build trust and profits

(Keeling et al., 2010).

Visualization enables streamers and users to conduct face-to-text communication in live streaming commerce (Sun et al., 2019). It enables the streamer the ability to being different communication styles of offline salespersons online. Given that the pivotal aspect of live streaming commerce is the interaction between streamers and audiences, this study only concentrates on the interaction orientation of streamers (Liao et al., 2022). Therefore, this study regards interaction orientation communication style as a key factor of streamer attributes.

2.6.4 Key Highlights of Streamer Attributes

With the emergence of live streaming commerce, streamers, as a new profession, have become the content creators and core of live streaming commerce. Streamers can be seen as spokespeople or salespersons of brands or products. Meanwhile, previous studies have shown that communicator attributes and communication styles can have positive or negative effects on relationship building and the persuasiveness of messages (Crosby et al., 1990; Darian et al., 2005; Li & Peng, 2021). Based on the previous literature review, this study proposes that in order to better understand streamer attributes, expertise, attractiveness, and interaction orientation should be included. Each component is summarised as follows.

- Expertise: streamers' knowledge, experience, qualifications, and achievements in live streaming or selling related products.
- Attractiveness: streamers' pleasing physical feature and attractiveness.
- Interaction orientation: streamers' active interaction with the audience.

2.7 Technical Attributes

2.7.1 Technical Attributes in Online Marketplace

The objectives of e-commerce design encompass enhancing customer engagement, aiding customer decision-making, and fostering customer loyalty (Cao et al., 2005). It is therefore reasonable to delve into the technical features of e-commerce through the user's viewpoint (Liu & Arnett, 2000). This section focuses on reviewing the technical attributes of e-commerce platforms from a human-computer interaction (HCI) perspective. The findings of the review reveal that the technical attributes of e-commerce are mainly represented through different dimensions of information quality, system quality, and service quality (refer to Table 2.4).

Table 2.4 : Summary of Technical Attributes in Online Marketplace

Categories	Attributes	Meaning	References
Information quality	Relevance	Offer relevant information	(Aladwani & Palvia, 2002; Jaiswal et al., 2010)
	Accuracy	Offer accurate information	(Aladwani & Palvia, 2002; Cao et al., 2005; Jaiswal et al., 2010)
	Completeness	Offer complete information	(Liu & Arnett, 2000)
	Update	Offer current information	(Hasan & Abuelrub, 2011)
	Authority	Instil trust in information for users.	(Hasan & Abuelrub, 2011)
	Objective	Offer impartial and unbiased information	(Hasan & Abuelrub, 2011)
	Usefulness	Offer useful information	(Liu & Arnett, 2000; Susser & Ariga, 2006)
	Sufficiency	Offer sufficient information	(Jaiswal et al., 2010; Lee & Dubinsky, 2003)
System quality	Security	Guarantee the execution of tasks with a focus on security	(Lee & Kozar, 2006; Liu & Arnett, 2000)

Table 2.4 : Continued

Access	Facilitate rapid service accessibility.	(Liu & Arnett, 2000)
Error recovery	Assist in the recovery from errors.	(Liu & Arnett, 2000)
Operation	User-friendly system and services	(Liu & Arnett, 2000)
Appearance	Display visual design components	(Lee & Kozar, 2006; Robins & Holmes, 2008)
Functionality	Offer rich functions	(Cao et al., 2005)
Payment	Offer secure and convenient payment options	(Liu & Arnett, 2000)
Ordering mechanism	To handle user orders and track their status	(Liu & Arnett, 2000)
Content	Offer high-quality content that meets user expectations	(Liu & Arnett, 2000)
Ease of use	The website easy to use and operate	(Belanger et al., 2002; S. Lee & Dubinsky, 2003; Nielsen, 1994)
User-friendliness	Website interface is easy for users to navigate and interact with.	(Matera et al., 2002)
Simplicity	Website owns simple structure and functions	(Flavián et al., 2006; Helander & Khalid, 2000; Nielsen, 1994)
Navigation	Assist users in navigating the website	(Flavián et al., 2006; Hasan & Abuelrub, 2011)
User control	User can exit site at any given moment	(Flavián et al., 2006; Nielsen, 1994)
Error prevention	Avoiding error by users	(Nielsen, 1994)
Help function	Provide assistance and documentation	(Helander & Khalid, 2000; Nielsen, 1994)
Understandability	The content of website easy to understand	(Flavián et al., 2006; Hasan & Abuelrub, 2011)
Accessibility	The website is accessible for all users	(Helander & Khalid, 2000)
Speed	Load items quickly	(Flavián et al., 2006)
Visibility of system status	Provide users with regular updates and information about the system	(Helander & Khalid, 2000; Nielsen, 1994)
Match real world	Follow real-world regulations	(Nielsen, 1994)
Consistency	Maintain consistent design elements across the entire website	(Nielsen, 1994)

Table 2.4 : Continued

	Recognition rather than recall	Facilitate easy retention of information.	(Nielsen, 1994)
	Aesthetic design	Websites with appealing and visually pleasing designs.	(Nielsen, 1994)
	Personalisation	Allow users to personalise and modify the site according to their preferences.	(Helander & Khalid, 2000)
Service quality	Responsiveness	Respond to user requirements quickly	(Cao et al., 2005)
	Assurance	Offer support for user problem solving	(Liu & Arnett, 2000; et al., 1994.
	Empathy	Offer users with care and attention	(Cao et al., 2005)
	Following up service	Listen to user feedback	(Liu & Arnett, 2000)
	Reliability	To provide dependable and trustworthy services	(Heim & Field, 2007; Lee & Kozar, 2006)
	Intrinsic interest	To cater to user interests	(Katerattanakul, 2002)

Information quality refers to the relevance, accuracy, clarity, and usefulness of information provided by e-commerce websites, serving as a source of value for customers in e-commerce (Kuan et al., 2008; Pavlou & Fygenson, 2006). Jaiswal et al. (2010) demonstrated that information quality is a pivotal factor affecting user loyalty in e-commerce. Hence, prioritising information quality to furnish precise, sufficient, and pertinent information is imperative. Liu and Arnett (2000) underscored the significance of information quality, linking it closely to business profitability, decision-making efficacy, system performance, and user acceptance. Users' perceptions of system benefits and acceptance are heavily reliant on the availability of distinct, dependable, and current information. High-quality information enable a broader range of users to embrace information systems, especially e-commerce platforms (Cao et al., 2005). Therefore, information quality emerges as a pivotal technical attribute in e-commerce, encompassing precision, timeliness, relevance, flexible information presentation, pricing transparency, product comparability, and comprehensive product descriptions.

System quality refers to how effectively an e-commerce platform operates in providing information and services (Kuan et al., 2008). It greatly influences customer satisfaction (Chu et al., 2007), trust (Kong et al., 2020), and purchasing behaviour (Liao et al., 2006). Common dissatisfaction among customers regarding e-commerce websites include slow loading speeds, inadequate error resolution, limited operational and computing capabilities, and insecure services (Cao et al., 2005). Conversely, improving website quality entails focusing on elements such as design, content, functionality, navigation, and security. Specifically, appearance involves the visual presentation of a website, leveraging various design elements like text size, colour, layout, and fonts to enhance visual appeal (Liao et al., 2006). Content serves as a valuable source of information for customers and should be kept current, comprehensive and accurate (Kuan et al., 2008). Functionality encompasses attributes that fulfil customer needs in accomplishing tasks (Huang & Benyoucef, 2013). Navigation assists customers in identifying navigational controls for moving around the site (Pavlou & Fygenson, 2006). Lastly, security guarantees that users can interact with the intended service securely and perform tasks without risk (Belanger et al., 2002).

Service quality refers to the ability of an online provider to offer supportive features in e-commerce (DeLone & McLean, 2004), such as FAQs, order tracking, and complaint handling. Inadequate support can result in customer and sales losses (Cao et al., 2005). Various studies have aimed to comprehend the design of service quality by examining its components. For instance, Lee and Kozar (2006) outlined empathy, reliability, and responsiveness as key attributes of service quality. Moreover, service quality emphasises reliability, assurance, responsiveness, empathy, and tangibility when assessing service quality (Heim & Field, 2007). Reliability entails offering dependable and trustworthy services. Responsiveness involves meeting customer needs promptly and effectively. Empathy demonstrates vendors' capacity to engage with customers. Assurance is demonstrated through effective problem-solving and encompass a range of physical facilities.

In conclusion, the existing empirical research on the technical attributes of e-commerce focuses on different aspects of information quality, system quality and service quality. However, not all attributes are suitable for implementation in live streaming commerce. The next section will identify the technical attributes of live streaming commerce by comparing the differences between e-commerce and live streaming commerce.

2.7.2 Technical Attributes of Live Streaming Commerce

Live streaming commerce differs from traditional online shopping. Drawing from prior literature on live streaming commerce, Table 2.5 summarises and illustrates these differences. Firstly, unlike traditional online shopping, product information and services in live streaming commerce are predominantly provided by streamers, who have become the principal creators of information and providers of services in live streaming commerce (Chen et al., 2023; Guo et al., 2022; Liao et al., 2022). Therefore, when considering the technical attributes of live streaming commerce, this study only considers system quality, excluding service quality and information quality in traditional e-commerce, as the latter two are characterised through the streamers.

Moreover, in traditional online shopping, consumers can only assess products through pictures, text descriptions, and pre-recorded videos provided by online vendors (Wongkitrungrueng et al., 2020). Conversely, in live streaming commerce, consumers can not only access product information through traditional pictures and text, but also through real-time videos in live streams (Gu et al., 2023). Real-time video enables consumers to obtain richer and more detailed product information compared to traditional e-commerce (Liu & Sun, 2023). Hence, media richness, a crucial attribute of communication media, could be a significant distinguishing feature of live streaming commerce compared to traditional e-commerce.

Furthermore, traditional online shopping primarily relies on keyword searches to find products of interest to users (Wongkitrungrueng et al., 2020). With the assistance of artificial intelligence, machine learning, and big data technology, smart recommendations systems based on user profile and history have become the primary method for users to discover products of interest in live streaming commerce (Sun et al., 2019). Consequently, platform personalisation has emerged as another key technical attribute of live streaming commerce.

In general, this study focusses on media richness and personalisation as the primary technical attributes of live streaming commerce.

Table 2.5 : Comparison of e-Commerce and Lives Streaming Commerce

Shopping type	Traditional online commerce	Live-streaming commerce
Medium	Text, images, and pre-recorded videos that can be edited.	Text, images, and live videos that are difficult to edit (Wongkitrungrueng et al., 2020)
Immediate feedback	Asynchronism	Synchronism (Wongkitrungrueng et al., 2020)
Multiple cue	Interaction with vendors through text-to-text written communication. Limited verbal communication (Benedicktus et al., 2010)	Face-to-text communication with verbal responses from streamers. Beside text, image, and digital symbols, streamers' voice, tones, and gesture can be seen (Chen et al., 2023)
Language variety	Limit language variety, only text-to-text written communication.	Emojis, likes, shares, and gifts enable meanings can be communicated
Get interested products	Search keywords (Wongkitrungrueng et al., 2020)	Platform personalise recommendations based on user history
Information Source	Information provided by website	Streamer is the content creator and source of information (Chen et al., 2023)
Service Source	Service provided by website	Streamers provide service through real-time live streaming

2.7.3 Media Richness

The media richness theory (MRT), first introduced by Daft and Lengel (1986), asserts that the efficacy of communication media in delivering information is determined by their functional attributes. In other words, richer media have the ability to convey a greater amount of information (Daft et al., 1987; Daft & Lengel, 1986; Tseng & Wei, 2020). Media richness refers to the extent to which information is transmitted and its ability to reproduce the transmitted content (Daft & Lengel, 1986). In addition, the MRT further suggests that the goal of communication is to eliminate uncertainty and ambiguity to communicate efficiently (Daft et al., 1987).

According to Kahai and Cooper (2003), media richness lies in a channel's ability to provide immediate feedback, multiple cues, variety language, and personalised focus.

More specifically, immediate feedback refers to the way the media enables individuals to react quickly to messages they receive. The quicker the media feedback throughout the communication process, the more it aids users in correcting each other's knowledge to guarantee effective information processing (Chidiac & Bowden, 2023; Lee et al., 2009). Second, multiple cues encompass the number of cues that can be used to communicate, i.e., whether they can meet the various requirements of different users in terms of information reception methods via diverse delivery modes and assist users in communicating more accurately (Chidiac & Bowden, 2023; Lee et al., 2009). This includes, for instance, physical presence, voice changes, physical gestures, text, numerical and visual symbols. Third, language variety is described as the ability to communicate in a language using symbols or in different ways (Liao et al., 2020). Lastly, personal focus means the extent to which a communicator can tailor information to the recipient's needs and circumstances (Lee et al., 2009; Ogara et al., 2014; Trevino et al., 1987).

Communication media differ in their ability to convey rich information. Daft et al. (1987) categorised media as a continuum that is "potentially rich in information" , with four distinct types along this continuum: text, audio, video, and face-to-face communication (see Figure 2.7). Face-to-face communication is the richest medium due to its ability to simultaneously transmit various forms of information via body language, facial expressions, and tone of voice (Daft et al., 1987). In contrast, text-based media, such as texting on a mobile device, are referred to as lean media (Maity & Dass, 2014). Today, electronic media offer a range of video clips, quick responses, and the use of natural language to increase media richness (Vickery et al., 2004). Similarly, Vazquez et al. (2017) claim that mobile instant messaging (MIM) channels like WeChat incorporate features like location-based services (LBS), voice messages, and moment sharing to enhance media richness.

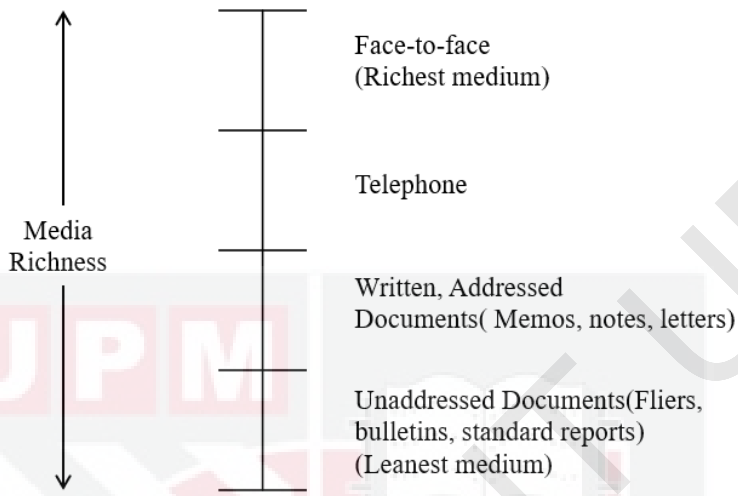

Figure 2.7 : Theory of Media Richness
(Source: Daft & Lengel, 1986)

The MRT has been utilised across different contexts, including online commerce (Chen & Chang, 2018), influencer marketing (Chidiac & Bowden, 2023), online gaming (Tseng et al., 2022), social media (Sheer, 2010, 2011), and MIM (Tseng et al., 2019). Media richness has been shown to lead to positive consumer behaviour. For example, research in online communication has demonstrated that media richness improves self-presentation and fosters interpersonal relationships among users of online platforms (Lee & Borah, 2020), indicating the significance of MRT in analysing current online communication tools. Likewise, researchers in online commerce argue that higher media richness helps satisfy e-commerce consumers' information demands and promotes them to buy by minimising ambiguity (Chen & Chang, 2018; Liao et al., 2020). In advertising, conveying more information through media richness may lead to more positive advertising impacts (Lim & Benbasat, 2000).

These results coincide with the idea suggested by Tseng and Wei (2020), who examined the influence of media richness on different stages of the AISAS (attention, interest, search, action, share) model in mobile advertising marketing. Their study revealed that media richness had a greater effect on the initial three stages of AISAS than the later stages. Consequently, it suggests that enterprises implementing mobile advertising should leverage media richness to target clients in the early stages of their consumer behaviour (Tseng & Wei, 2020).

Online commerce relies solely on the information presented on websites, which shoppers cannot physically see or touch, thus limiting their perception of the product. In this regard, the website's media richness is crucial, as users can understand products through a variety of cues that are shockingly broader and deeper than expected (Chen & Chang, 2018; Liao et al., 2020). Furthermore, Jiang and Benbasat (2007b) assessed that media richness in online e-commerce mainly lies in the ability to provide comprehensive information about the product to be delivered. Therefore, based on Daft and Lengel's (1986) concept of media richness and by incorporating Jiang and Benbasat's (2007b) perspective, this study proposed that media richness refers to the level of communication capability that live commerce can offer to users. Specifically, media richness manifests in four aspects in live streaming commerce.

Immediate feedback: The real-time of live streaming enables users to rapidly respond to received messages.

Multiple cues: Read-time video presentation of live stream commerce enable streamers and users convey messages, including text, images, language, voice tone, digital symbols, and body language.

Language variety: Live streaming commerce contains emojis, likes, shares, and gifts, where meanings can be communicated through symbols or alternatives.

Personal focus: Livestream commerce allows users to articulate their personal emotions or feelings and customise messages to fit the requirements or circumstances of receivers.

Different cultures place varying levels of importance on media richness. Scholars argue that in high-context cultures (such as China), people require more cues and immediate feedback in communication compared to low-context Western countries (Hall, 1976). On the other hand, the higher the level of uncertainty avoidance, the greater the need for cues, immediate feedback, personal focus, and linguistic diversity (Hall, 1976; Illia & Lawson, 2007). Therefore, as a culture characterised by high context and high uncertainty avoidance, Chinese live streaming commerce users may require more features related to media richness to effectively communicate both verbal and non-verbal cues, facilitating more productive interactions in an ambiguous e-commerce environment.

Live streaming commerce primarily serves the essential function of showcasing products. It builds a virtual scene with a three-dimensional spatial sense to compensate for users' inability to physically touch the products. The "Live Room Setting" module provided by technical service providers integrates various forms of information like video clips, product images, textual displays, and automated responses, effectively disseminating diverse information through the platform. Thus, media richness represents the technical attributes of live streaming commerce, transforming it into an information system that transfers information to customers and assists them in making decisions through this channel. In summary, media richness is considered a critical technical attribute of live streaming commerce.

2.7.4 Personalisation

Personalisation originates from the market segmentation theory proposed by the American marketing scholar Wendell Smith (1956), which suggests that consumers in different market segments have varying product needs and desires. Over time, personalisation has become the cornerstone of modern marketing. With the rise of e-commerce and the advancements of information technology, personalised recommendation technology has enabled platforms to gather and utilise user information to offer tailored content and services that align with users' preferences. For instance, Amazon utilises multiple cookies on users' computers to track their behaviour and deliver a personalised experience. This study focuses on personalised recommendation, adopting Tam and Ho's (2005) definition: "the use of personalisation techniques to deliver the right content to the right person in the right format at the right time".

Previous scholars have extensively investigated the role of personalisation in online commerce. Studies have shown that consumers are more inclined to accept personalised recommendations, as opposed to non-personalised ones, which are generated without considering consumer preferences (Senecal & Nantel, 2004) than non-personalised recommendations (i.e., recommendations generated without consideration of consumer preferences). Personalised recommendations also lead to more clicks than random recommendations (de Pechpeyrou, 2009) and higher user ratings compared to random recommendations (Panniello et al., 2017). Additionally, they contribute to a substantial rise in page views and sales for mobile commerce. This is because customers believe that personalised recommendations from the platform are more self-relevant and content-relevant (Tam & Ho, 2006), helping them better understand products (Komiak & Benbasat, 2006), thereby saving shopping time and making the buying process easier and more enjoyable for consumers (Aljukhadar & Senecal, 2011; Xiao et al., 2019). Similarly, the study conducted by Komiak and Benbasat (2006) further clarify that personalised recommendations make users perceive the care and empathy of the website, thus increasing customers' trust and adoption of the recommendation agent.

In the context of live streaming commerce, previous research have highlighted personalisation from streamers in the consumer decision-making process. For example, Sun et al.'s (2019) research emphasised that personalisation from streamers provides a more immersive experience for users. In the same vein, a study conducted by Xue et al. (2020) demonstrated that personalisation from streamers is more effective in capturing consumers' attention, providing more useful information about the product or service, and helping them to better accept marketing campaigns. However, the role of personalised recommendations from the platform has been less explored.

Nowadays, content-sharing platforms such as Douyin use smart intelligence systems to make personalised recommendations (Wang et al., 2023, 2023). With the assistance of artificial intelligence, machine learning, and big data technology, smart recommendation systems can suggest personalised live rooms and products based on users' profiles and preferences. Automatically suggesting products that align with users' expectations can also reduce the time and effort they spend on product selection (Aljukhadar & Senecal, 2011; Xiao et al., 2019), which is crucial for facilitating purchase decisions. Therefore, this study proposed that personalisation is another technical attribute of live streaming commerce.

2.7.5 Key Highlights of Technical Attributes in Live Streaming Commerce

With the emergence of various online marketing platforms, including e-commerce and live streaming commerce, different requirements are placed on technical attributes. Based on the previous discussion, an overview of the literature advocates a better understanding of the technical attributes of live streaming commerce platforms by incorporating media richness and personalisation as key components.

2.8 Swift Guanxi

Swift guanxi is considered an important component of relationship marketing strategies in the Chinese market. Existing literature suggests that swift guanxi is one of the psychological mechanisms that stimulate customers to purchase and repurchase (Shang & Bao, 2022; Zhou et al., 2022), as well as foster positive word-of-mouth and sharing intentions (Cheng et al., 2020; Fan et al., 2019). Swift guanxi is an emerging research area in marketing literature within the Chinese cultural context. Therefore, it is considered equally relevant to the context of live streaming commerce.

2.8.1 The Difference between Relational Exchange and Guanxi

Relationship quality refers to the intimacy or strength of a specific relationship, measuring the depth of the buyer-seller relationship and predicting future interactions between the parties (Crosby et al., 1990). Consequently, it serves as a vital indicator of the health of the buyer-seller relationship (Huang et al., 2014). Previous research has shown that high consumer-firm relationship quality can yield positive outcomes, such as increased sales and customer loyalty (Athanasopoulou, 2009; Palmatier et al., 2006). In the realm of information systems research, relationship quality holds particular importance in online purchasing, as it influences repurchase intention (Verma et al., 2016) and improves the willingness to purchase or share intention (Hajli, 2015; Hossain et al., 2020).

Relationship quality manifests in different forms and cultural contexts. In the Western culture, relationship quality is frequently conceptualised and operationalised as trust, satisfaction, and commitment (Sheikh et al., 2019; Verma et al., 2016). Yet, China has a distinct cultural setting from Western culture. China is heavily influenced by Confucianism, which emphasises the importance of building harmonious, long-term “guanxi”. "Guanxi" has been a way of life for the Chinese since ancient times, and building and maintaining good guanxi is seen as an unavoidable aspect of business (Bilal et al., 2022; Wong & Tam, 2000). In other words, interpersonal relationships in the Chinese business environment are referred to as guanxi, which signifies a relationship based on mutual obligations and benefits (Shi et al., 2018). Especially in the context of social commerce, the development of institutional mechanisms lags behind the expansion of social media (Fan et al., 2019). In this context, businesses in China rely more on the interpersonal guanxi between the transacting parties to reduce the uncertainty in the transaction as the related parties believe that the other party is not opportunistic towards them.

Considering the complexities of the concept of guanxi, it can be divided into four categories: (1) personal relationships, (2) close relationships (e.g., relatives and friends) (Farh et al., 1998), (3) social networks (Luo et al., 2008), and (4) mutual benefit relationships (e.g., interpersonal trust and face protection) (Ou, Pavlou, & Davison, 2014). Specifically, the following are the key contrasts between guanxi in the Chinese context and relationship exchange in the Western context.

First, guanxi is more personal and mostly based on friendship. Swift guanxi is a personal connection based on personal care and reciprocal communication. In other words, it emphasises emotional values more than monetary ones. In contrast, for relational exchange, economic or impersonal involvement is essential. Therefore, it generates commitment and relational expectations based on the calculation (Lin et al., 2018).

Second, rather than being a general term, "guanxi" refers to a relationship specific to networks, where partners are connected through mutual obligations and the exchange of favours. Relationship exchange is a general rule that allows any partner to enter the network as long as the corresponding rules are followed, whereas guanxi is very network-specific and does not often open to members of other social networks (Lin et al., 2018).

Third, moral and social norms serve as the guiding principles of guanxi, whereas legality and rules govern relational exchanges in Western culture (Lin et al., 2018). According to one report (CNNIC, 2021), social network platforms like WeChat are used to foster guanxi. Therefore, guanxi represents a key factor in interpersonal relationships within the Chinese business environment.

Previous studies have shown that guanxi has a positive impact on market success in conventional businesses (Gu et al., 2008). This can be explained for a variety of reasons, including enhancing consumer value perception (Wang, 2007), minimising uncertainty and risk (Leung et al., 2005), and increasing trust and loyalty (Chen et al., 2004; Lee et al., 2018; Palmatier et al., 2006).

2.8.2 Definition and Operationalisation of Swift Guanxi

Ou et al. (2014) introduced the term swift guanxi based on the nature of online marketplaces as online consumers do not spend much effort developing relationships with sellers. Swift guanxi refers to the reciprocity-based interpersonal relationships that buyers form quickly with sellers in online marketplaces (Shang & Bao, 2022). In particular, there are four main differences between swift guanxi and traditional guanxi (see Table 2.6) (Lin et al., 2019; Ou et al., 2014).

First, the swift nature of guanxi is the primary distinction. While traditional guanxi is geared toward long-term partnerships, online buyers are less inclined to dedicate extensive time to establishing connections with online sellers (Ou, Pavlou, & Davison, 2014). They may switch to a different seller if they are unable to check product qualities with a particular seller (Chou et al., 2016). Second, restricted resources are crucial for the establishment of traditional guanxi (Arias, 1998). However, the increasing access to alternative products and services in online markets has reduced reliance on any one seller (González-Benito et al., 2015). Resources are less important for building swift guanxi because it is established quickly and does not rely on them.

Third, in social commerce, buyers and sellers have nearly equal status as they interact together, and there are no difference in resources (Zhang et al., 2016). However, status is significant in traditional guanxi because senior individuals tend to have greater resources. Fourth, while traditional guanxi is built mainly through face-to-face communication, swift guanxi is formed based on online computer-mediated communication (CMC) tools (Liu et al., 2008; Ou et al., 2014). Therefore, due to the fundamental traits of online transactions and immediate relational demands of Internet users, swift guanxi differs from traditional guanxi.

Table 2.6 : Difference between Swift Guanxi and Traditional Guanxi

Characteristics	Swift guanxi	Traditional guanxi
Relationship continuity	Short term	Long term
Status	Independent	Dependent
Communication Mode	Computer-mediated	Face to face
Time and energy required	Less	More
Applicable environment	Online	Offline

Additionally, some scholars have proposed the concept of long-term e-guanxi or online guanxi in social commerce. Wu et al. (2022) argued that the guanxi between parties is not always swift in social commerce, suggesting that the concept of swift guanxi may not fully capture the characteristics of buyer-to-seller (B-S) guanxi. This view is supported by Zhou et al. (2024), who note that many relationships still rely on ongoing social interactions and prior connections rather than solely on immediate exchanges typical in social commerce. Their findings further indicate that each aspect of guanxi (i.e., ganqing, renqing, and mianzi) positively influences seller's influence effectiveness, but only renqing significantly enhances purchase intention (Wu et al., 2022). In contrast to swift guanxi, e-guanxi more comprehensively considers buyers' perceptions of informal risk mitigation based on the expected consistency of sellers' communications and behaviours, which relates to trust (see Figure 2.8).

As a subset of social commerce, live streaming commerce encompasses both swift guanxi and e-guanxi. This aligns with Ou et al.'s (2014) view that while swift guanxi helps explain buyers' willingness to engage in transactions, it does not exclude the potential for accumulating guanxi over time, which can lead to long-term effects. In other words, swift guanxi is a process rather than an instantaneous event. However, due to the short duration of user stay in live streaming, users may hesitate to invest substantial time in building guanxi with online streamers (Chen et al., 2022; Ou, Pavlou, & Davison, 2014). If they cannot verify product features with one streamer, they may quickly switch to another. Consequently, buyers often aim to form quick and relatively superficial relationships with streamers, as swift guanxi can create psychological comfort with the seller and facilitate transaction completion (Chong et al., 2018; Lin et al., 2017; Shi et al., 2018). Therefore, this study focuses specifically on swift guanxi.

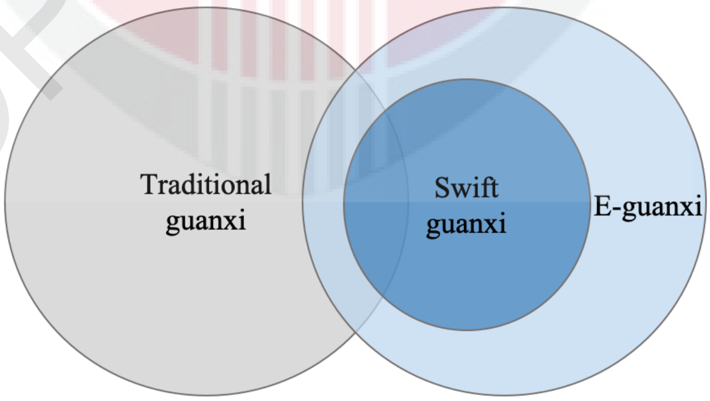

Figure 2.8 : Traditional Guanxi, Swift Guanxi and E-Guanxi
(Source: Daft & Lengel, 1986; Zhou et al., 2024)

Ou et al. (2014) introduced three dimensions of swift guanxi: mutual understanding, reciprocal favours, and relationship harmony, which have been widely embraced by subsequent scholars (Fan et al., 2019; Tseng et al., 2022).

Mutual Understanding

Mutual understanding serves as the foundation for relationship building as it allows buyers and sellers to comprehend each other's needs (Ahmed et al., 2013; Wu & Wang Chiu, 2016). CMC helps online firms better comprehend client expectations on pricing, product details, and delivery (Ou, Pavlou, & Davison, 2014), encouraging mutual understanding between sellers and customers. Meanwhile, relationships between buyers and sellers strengthen as they get to know each other. Hence, mutual understanding, with the help of ICT, can facilitate swift guanxi.

Reciprocal Favours

Reciprocal favours are the favourable outcomes of the interaction between buyers and sellers (Lee & Dawes, 2005). They represent a unique aspect of swift guanxi that distinguishes it from both social capital and relationship marketing. In China, individuals emphasise responsibility and obligation in their social connections. As a result, guanxi is typically sustained through mutual exchanges, favour trading, and adherence to reciprocal norms (Ou, Pavlou, & Davison, 2014). In contrast to Western contexts, where favours are typically limited to concrete items like money, goods, or services, the favours associated with swift guanxi can encompass more abstract concepts such as opportunities and emotional connections (Hwang, 1987).

The social exchange theory posits that reciprocity is a key element of the benefits derived from social interactions. During online shopping, the mutual benefit of buyers and sellers can fulfil the demands of both parties, thereby completing the transaction's goal. To swiftly establish guanxi and expedite transactions, sellers often provide discounts and small gifts to entice customers. In return, buyers may be willing to provide favourable feedback and reviews to sellers (Ou, Pavlou, & Davison, 2014). In China's online marketplace, buyer discounts give customers the sense that they are getting a good deal. Online sellers, on the other hand, value positive customer reviews because online ratings are crucial to their success. Therefore, reciprocal favours are crucial components of swift guanxi, as they benefit both parties in online commerce.

In live commerce, some sellers provide extra freebies, discounts, or coupons to viewers, and they also respond positively to user requests, such as trying a certain colour of lipstick. Additionally, some platforms offer features that enable reciprocal interaction, such as virtual gifts. In other words, reciprocal favours may be gained through real-time face-to-text communication in live streaming shopping.

Relationship Harmony

Relationship harmony entails mutual respect and the avoidance of conflict. It is seen as an essential component of all relationships (Leung et al., 2002). Chinese society advocates and pursues harmony as its fundamental value, and Confucianism, which dominates Chinese culture and serves as its primary attitude orientation, places a high value on harmony (Su et al., 2003). In the context of live streaming commerce, sellers demonstrate care for buyers through real-time communication, attracting new customers and cultivating loyalty among existing ones.

Overall, swift guanxi represents a unique form of relational connection that quickly develops in Chinese cultural contexts, characterized by rapid mutual understanding, reciprocal favours, and relationship harmony (Ou, Pavlou, & Davison, 2014). Treating swift guanxi as a single construct allows it to be consistently conceptualized and measured as a unified outcome rather than as a sum of its parts, enhancing conceptual clarity. Although swift guanxi is influenced by various antecedents, such as interpersonal interaction factors and trust, each antecedent uniquely impacts relationship formation. Analyzing these antecedents individually clarifies their specific contributions to the development of swift guanxi.

2.8.3 Previous Research on Swift Guanxi

A literature review of swift guanxi indicates that it serves as a mediator in various contexts, including online commerce (Ou, Pavlou, & Davison, 2014; Shi et al., 2018), social commerce (Chong et al., 2018; Lin et al., 2017; Shi et al., 2018), online gaming (Tseng et al., 2022), and online communities (Jia et al., 2023; Liu et al., 2023) (see Table 2.7). For instance, Ou et al. (2014) argued that technological features enhance swift guanxi through interactivity and presence, thereby increasing repurchase intention. Similarly, Shi et al. (2018) noted that service quality contributes to building swift guanxi, which in turn fosters repurchase intention.

Additionally, some researchers emphasise swift guanxi's mediating role in predicting purchase intention. Lin et al. (2018) explored social support as a precursor to swift guanxi and trust, which influences social commerce intention. Likewise, Lin et al. (2019) found that social commerce affordances affect swift guanxi, ultimately leading to purchase intention. In fact, mutual understanding, reciprocity, and harmonious relationships between consumers and sellers can reduce uncertainty (Chiu et al., 2018) and create benefits for both parties (Ou, Pavlou, & Davison, 2014), thus fostering users' purchase intention. In general, previous research consistently indicates that swift guanxi can act as a mediator between technical characteristics, interpersonal factors, information quality, and favourable outcomes in online marketplace (Chong et al., 2018; Lin et al., 2017; Shi et al., 2018). However, there is a paucity of studies on the mediating role of swift guanxi that link digital attributes and decision-making in live streaming commerce (Lin et al., 2017).

Table 2.7 : List of Drivers and Outcomes of Swift Guanxi

Authors	Antecedents	Outcomes	Mediators	Context
Ou et al. (2014)	Effective use of instant messaging; Effective use of the message box; Effective use of feedback system	Repurchase intention	Swift guanxi	Online commerce
Lin et al. (2017)	Interactivity; Recommendation; Feedback	Repurchase intention	Swift guanxi	Social commerce
Lin et al. (2018)	Informational support; Emotional support	Social shopping intention; social sharing intention	Swift guanxi; Trust	Social Commerce
Chong et al. (2018)	Effective use of instant messaging; Effective use of the online reviews	Repurchase intention;	Swift guanxi	Social commerce
Shi et al. (2018)	Perceived control; Service convenience; Customer service	Repurchase intention	Swift guanxi	Online commerce
Fan et al. (2019)	Social support; Presence	Repurchase intention	Swift guanxi	E-Commerce
Lin et al. (2019)	Interactivity; Stickiness; Word of mouth	purchase intention	Swift guanxi	Social Commerce
Cheng et al. (2020)	Familiarity, Interpersonal Similarity, Interactivity; Personal information	SWOM adopting behaviour; SWOM behaviour	Swift guanxi; Commitment	Social commerce

Table 2.7 : Continued

Tseng et al. (2022)	Media richness; Interactivity; Presence	Online game loyalty	Swift guanxi	Games
Zhang et al. (2022)	Community interaction quality	Travel intention	Sense of community; swift-guanxi	Live streaming
Zhou et al. (2023)	Perceived informativeness; Perceived responsiveness; Perceived expertise; Perceived similarity	Purchase intention	Swift guanxi; Initial trust	Social commerce
Jia et al. (2023)	Monetary social functions; Non-monetary social functions	Knowledge sharing intention	Social capital; Swift guanxi; Social identity	Online social Q&A communities
Liu et al. (2023)	Server disclosure; Customer disclosure	Customer engagement	Swift guanxi; Trust	online restaurant community

2.8.4 Key Highlights of Swift Guanxi in the Live Streaming Commerce

Unlike relationship marketing in Western markets, China emphasises guanxi. As an online extension of traditional guanxi, swift guanxi has become an important mechanism for online marketplace success and ultimately stimulates positive behavioural outcomes (Ou, Pavlou, & Davison, 2014). For example, it has been consistently reported that clients who have swift guanxi with sellers are more willing to purchase and have positive eWOM (Cheng et al., 2020; Fan et al., 2019). In particular, swift guanxi is considered to be a key factor in mitigating consumer uncertainty, which in turn influences the behaviour of repurchase (Chiu et al., 2018). Existing research articulated swift guanxi on a three-dimensional scale, namely mutual understanding, reciprocal favour, and relationship harmony (Ou, Pavlou, & Davison, 2014). Therefore, this study draws on the conceptualisation of Ou et al. (2014) to examine how swift guanxi affects consumer behaviour in the context of live streaming commerce.

2.9 Boundary Conditions

Boundary conditions have been recognised as crucial in theory development, encompassing the who, where, and when aspects of a theory (Busse et al., 2017). These conditions primarily address limitations related to time, space, and the values of the researcher (Bacharach, 1989), outlining the scope of a model or theory's generalisability (Busse et al., 2017). Therefore, it is essential to acknowledge and define these boundaries.

2.9.1 Boundary Conditions in Live Streaming Commerce

A review of the live streaming commerce literature shows that boundary conditions need to be considered when predicting consumer behaviour. Specifically, the boundary conditions in the context of live streaming commerce mainly include two categories: personal-related moderators and marketing strategy-related moderators (Luo et al., 2023).

Individual-related moderators mainly include demographic factors (e.g., age, education, experience, gender, and income) and personal-related factors (e.g., self-construal, mindfulness, and perceived power) (Luo et al., 2023; Lv et al., 2022; Zhou et al., 2021). For example, Lv et al. (2022) used multigroup analysis to show that, driven by the desire to buy, females are more inclined to make impulse purchases than males. In addition, as live streaming interest increases, women are more likely than men to continue watching live streaming and recommend friends to continue watching live streaming. Similarly, the study of Zhou et al. (2021) shows that younger groups tend to develop behavioural intentions due to habits, while older subgroups are more inclined to form behavioural intentions due to convenient conditions. Additionally, compared with experienced viewers, viewers with less viewing experience are more inclined to make immediate purchases once they have a strong desire to buy. Some personal-related factors are also used as boundary conditions for consumer behaviour in live streaming commerce (Bao & Zhu, 2022; Gao et al., 2021; Lou et al., 2022; Xue et al., 2020). For instance, independent and interdependent self-construal (Hou et al., 2023), mindfulness (Gao et al., 2021), perceived power (Lou et al., 2022; Ming et al., 2021), impulsiveness (Alam et al., 2023) , and susceptibility to informational influence (Xue et al., 2020).

Furthermore, some marketing strategies have also been used as boundary conditions to study consumer behaviour in live streaming commerce, including product novelty (Liu et al., 2023), product self-fit (Ji et al., 2023), product involvement (Joo & Yang, 2023), product scarcity (Guo et al., 2023), and price involvement (Choi & Jeon, 2022). For example, regarding the moderating effect of time pressure, it was found that for viewers with low time pressure, as their perception of informativeness increases, they are more likely to be immersed in the live streaming than those with high time pressure.

While prior research on boundary conditions has provided useful insights into the field of live streaming commerce, it is worth noting that consumer behaviour is not independent of its institutional context (Bao et al., 2016; Huang et al., 2017). Prior research in traditional e-commerce suggests that different perceptions of e-commerce institutional context are an important boundary condition for measuring the effectiveness of relationship quality in predicting consumer behaviour (Fang et al., 2014; Tandon, 2023). For example, Chen et al. (2015) demonstrated that in situations where buyers perceive higher levels of PEEIM, those who have trust in the seller are inclined to develop a willingness to make a purchase from that particular seller in C2C online shopping context. However, content-sharing live streaming commerce originate from social media platforms, and the construction of e-commerce institutional safeguards has lagged behind the development of social media, which complicates users' perceptions of e-commerce institutional contexts (Lin et al., 2019). This has led researchers to call for further exploration of the moderating role of e-commerce institutional context on the relationship between relationship quality and consumer behaviour in the context of live streaming commerce (Bao & Zhu, 2022).

2.9.2 The Overview of PEEIM

Institutional mechanism is an impersonal structure established by third parties to ensure the success of transactions (Pavlou & Gefen, 2004). Institutional mechanisms come in many forms in the e-commerce environment. e-Commerce platform institutions typically exhibit characteristics such as prior compensation responsibility, identity authentication systems, and return and exchange system (Gefen et al., 2003). Fang et al. (2014) proposed the concept of perceived effectiveness of e-commerce institutional mechanisms (PEEIM), which refers to "online customers generally believe that there are protective measures within the e-commerce environment to safeguard them from potential risks in online transactions" (pp. 410).

PEEIM includes third-party assurance mechanisms, escrow services, and privacy protection. For example, online escrow services Alipay and PayPal release payment only when buyers receive satisfactory goods, thus guaranteeing transactions (Chong et al., 2018). Credit card online payment guarantees, provided by financial institutions such as credit card companies, offer compensation to buyers in cases of potential seller fraud (Pavlou & Gefen, 2004). In addition, Fang et al. (2014) suggest that PEEIM should be operated at a general level (i.e., independent of specific online sellers or vendors) to effectively address contextual uncertainty. PEEIM can be viewed as an uncertainty reduction strategy, indicating that their online transactions are safeguarded by institutional mechanisms against potential uncertainties (Chong et al., 2018; Tandon et al., 2021), hence being valued by buyers.

Previous literature highlights the significant importance of PEEIM in electronic commerce. Masri et al. (2021) examined the influence of trust-based mechanisms and PEEIM on purchasing intentions, revealing that PEEIM significantly affects online purchase intentions. Moreover, previous studies have also considered the moderating effect of PEEIM in e-commerce. For example, Fang et al. (2014) took Amazon as a sample to analyse the moderating effect between trust in vendor and repurchase intention in online commerce, and found that the link between trust in vendor and customer repurchase was negatively mediated by PEEIM. In other words, in environments where users have high PEEIM, e-commerce institutional mechanisms can mitigate situational risks, thereby reducing buyers' need for trust when they make purchases. Similarly, Chong et al. (2018) further verified that buyers' PEEIM negatively moderates trust in online sellers and repurchase intentions within the context of the Chinese e-marketplace Taobao. On the other hand, previous studies found that PEEIM also acts as a positive moderator. A study on consumer (C2C) online shopping platforms revealed that when buyers perceive high PEEIM, they believe the risk is low, and hope to achieve further mutual understanding through the exchange of information or emotional interaction, thereby fostering the formation of a strong tie (Dong & Wang, 2018). Likewise, in environments with high PEEIM, users who trust the sellers are more willing to form purchase intention with those sellers (Chen et al., 2015). Chen et al. (2022) further verifying the positive role of PEEIM in the context of social commerce. A high level of PEEIM reduces buyer uncertainty about the transaction, thereby facilitating swift guanxi to reduce perceived uncertainty more effectively.

2.9.3 Uncertainty Reduction Theory

The URT, initially proposed by Berger and Calabrses (1975), aims to explain how communication is used in the initial stages of interpersonal interaction to reduce uncertainty between individuals, thereby increasing the predictability of outcomes. The theory posits that unfamiliar communicators seek information to infer subsequent behaviours, and the accumulation of information typically involves self-disclosure and information sharing, which further enhances interpersonal relationships. URT (Berger & Calabrses, 1975) suggests that individuals adopt passive (observation) or active (information seeking) interactive strategies to reduce uncertainty. The passive approach to uncertainty reduction involves users relying on information provided by third parties to ensure the security of the environment they are in (Chen et al., 2022). Interactive strategies involve individuals initiating direct interpersonal communication with the object to acquire information to reduce uncertainty. In contrast, active strategies entail one party actively observing and drawing conclusions about their surroundings to gather information about the object (Berger & Calabrses, 1975).

The uncertainty brought by the online environment is the primary reason consumers are unwilling to make purchases. In this situation, URT has been widely applied across various online contexts, including social networking sites (Antheunis et al., 2010; Gambo & Özad, 2021), traditional e-commerce (Pavlou et al., 2007; Tang & Lin, 2019), and social commerce (Bai et al., 2015; N. Hu et al., 2008; Kanani & Glavee-Geo, 2021). URT is employed to elucidate diverse situations including interpersonal communication (Antheunis et al., 2010; Grace & Tham, 2021), organisational behaviour (Hu et al., 2008; Kramer, 1994; van den Bos & Lind, 2002), and user behaviour (Bai et al., 2015; Chen et al., 2023; Srivastava & Chandra, 2018). For instance, Maruping et al. (2019) proposed the utilisation of passive and interactive strategies by developers to mitigate uncertainty within open-source software communities. Likewise, in the context of traditional e-commerce, Tang and Lin (2019) examined the influence of three communication strategies on uncertainty reduction and intention to checkout. Regarding social commerce, Chen et al. (2023) posited that perceived information transparency across three dimensions (i.e., perceived product transparency, perceived seller transparency, and perceived transaction transparency) serve as an uncertainty reduction strategy that fosters positive purchase behaviour. The study by Chen et al. (2022) holds the same view and proposes PEEIM, swift guanxi, and situational normality as three reduction strategies that can promote positive social commerce purchase behaviour by reducing perceived uncertainty.

URT fundamentally focuses on how individuals reduce uncertainty in new situations. In the context of online commerce, perceived uncertainty refers to the extent to which buyers are unable to accurately predict the outcome of a transaction due to uncertainty regarding the seller, product, transaction process, or system-dependent uncertainty

(Grabner-Kraeuter, 2002). URT emphasises the proactive strategies that individuals use to gather information and alleviate this uncertainty. Therefore, it can explain how customers seek information about institutional mechanisms (e.g., reviews, guarantees, or privacy policies) to feel more secure in their decisions (Chen et al., 2022). In this sense, PEEIM can be viewed as an uncertainty reduction strategy that mitigates users' perceptions of uncertainty in live streaming commerce environments, addressing issues like privacy concerns and transaction uncertainty (Dong & Wang, 2018). In comparison, while the perceived risk theory from TAM is a robust framework for explaining consumer behaviour, it focuses only on individual risk factors associated with technology use, lacks emphasis on building trust through institutional mechanisms, and fails to account for customers' proactive information-seeking behaviours aimed at reducing uncertainty (Dowling & Staelin, 1994). Overall, URT provides a robust framework for understanding these behaviours (e.g., PEEIM) as effective means of reducing uncertainties (Chen et al., 2015).

2.9.4 Key Highlights of PEEIM in Live Streaming Commerce

Institutional mechanisms are one of the key factors driving the success of transactions in online marketplaces. Unlike previous institutional mechanisms that emphasise protection and assurance, Fang et al. (2014) introduced PEEIM and considered it a third-party guarantee mechanism, highlighting its uncertainty reducing effects. Additionally, compared to other forms of institutional mechanisms, PEEIM operates at a general level and is independent of sellers and platforms. In recent marketing research, PEEIM has emerged as a key factor associated with response. As an uncertainty reduction strategy, PEEIM not only directly influences consumer purchasing behaviour, but has also been shown to moderate the relationship between trust, satisfaction, and positive consumer behaviour in e-commerce, social commerce, and m-commerce (Chen et al., 2015; Chen et al., 2022; Fang et al., 2014). Users with high PEEIM are more conducive to interaction to form strong relationships (Dong & Wang, 2018), create experienced-based trust (Fang et al., 2014), and enhance the relationship between trust and purchase intention (Chen et al., 2015). Thus, incorporating the URT can help this research identify the moderating effects of PEEIM in the context of live streaming commerce.

2.10 Purchase Intention

The concept of purchase intention stems from behavioural intention, which refers to the likelihood of an individual engaging in a specific behaviour (Ajzen & Fishbein, 1975). Research suggests that behavioural intention serves as a more significant predictor of future actions than actual behaviour (Ajzen, 1991; Pavlou & Fygenson, 2006). In other words, behavioural intention is a prerequisite for action (Ajzen, 1991). Purchase intention is specifically defined as "the readiness and willingness of an individual to buy a particular product or service" (Ajzen, 1991). This indicates that consumers will assess their needs, gather relevant information, evaluate different options, and ultimately make a purchasing decision (Akar & Nasir, 2015; Chang & Wildt, 1994). Pavlou and Gefen (2004) further describes online purchase intention as the customer's interest and willingness to transact in online commerce.

Existing literature has investigated the factors influencing purchase intention, including consumer characteristics, seller attributes, and the features of stores and websites (Chan et al., 2017; Iyer et al., 2020). Scholars argue that the online shopping environment often promotes purchase intention more effectively than offline shopping, as it alleviates constraints associated with physical stores—such as inconvenient locations, limited hours, and social pressures from staff and other customers (Akar & Nasir, 2015; Chang et al., 2005). Furthermore, some researchers highlight the role of environmental cues, suggesting that both social and technical factors within the shopping environment impact purchase intention (Hu et al., 2016; Zhang et al., 2019).

Specifically, some studies indicate that social factors, including social influence, subjective norms, and peer attributes, significantly affect users' intentions to purchase products. Users' perceptions of others' attributes and attitudes toward purchasing in online environments impact their own willingness to buy, where more favourable perceptions lead to more positive purchase intentions (Hu et al., 2016; Zhang et al., 2019). These insights are consistent with various theoretical models, such as the Theory of Planned Behaviour (TPB) (Ajzen, 1991), the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003) and the socio-technical theory (Trist et al., 1963), all of which emphasise the influence of social factors on behavioural intention.

In addition to social influences, existing research has also focused on technical factors affecting purchase intention, such as information quality, perceived ease of use, usefulness, online atmosphere, and reliability. The online atmosphere, which includes structure, design, layout, functionality, image, and aesthetics, has a significant relationship with online purchase intention (Amiri Aghdaie et al., 2011; Chen & Teng, 2013). Research has shown that higher levels of media richness, ease of use, and reliability in online commerce enhance users' purchase intentions (Chen & Chang, 2018; Vahdat et al., 2021). Similar factors like perceived usefulness, effort expectancy, and performance expectancy also play a role in influencing users' willingness to purchase. If users believe that a product will enhance their performance and require minimal effort, they are more likely to proceed with the purchase (Mäntymäki & Salo, 2013). As outlined by the TAM (Davis, 1989), UTAUT (Venkatesh et al., 2003) and socio-technical theories (Trist et al., 1963), factors such as perceived usefulness, perceived ease of use, and effort expectancy impact users' online purchasing behaviour.

In conclusion, to effectively achieve successful marketing outcomes for sellers in live streaming commerce, it is crucial to focus on both social and technical factors in the live shopping context (Vahdat et al., 2021). Previous research has demonstrated that these factors significantly influence online users' purchase intentions (Hu et al., 2016; Zhang et al., 2019). This study adopts the definition by Sun et al. (2019), which describes purchase intention as the intent of customers to buy products or services from sellers through live streaming shopping.

2.11 Research Gaps

With the development of information technology, live streaming commerce has brought new experiences to users as a new sales model. At the same time, live streaming commerce has provided brands and retailers with more opportunities to build intimate relationships with users. Although live streaming commerce has experienced extensive growth in recent years, reports show that a large number of streamers have experienced failures in implementing live streaming commerce, where they are not accepted by users or fail to convert viewers into consumers (Chanmama, 2022; iiMedia, 2022). In academia, existing research has focused mainly on the adoption and user engagement in live streaming commerce (Kang et al., 2021; Lin et al., 2021; Liu et al., 2021; Wongkitrungrueng & Assarut, 2020; Xue et al., 2020), and factors that influence consumer purchase intention remain largely ignored (Sun et al., 2019). Therefore, this study attempts to bridge the gap by exploring the factors that drive consumers' purchase intention in live streaming commerce. Specifically, the research gaps in this study are divided into two parts: theoretical and contextual. These gaps are explained in detail below.

2.11.1 Theoretical Gap 1: Drivers of Purchase Intention

In this study, the first theoretical gap aims to explore the underlying factors that influence purchase intention in live streaming commerce. Purchase intention is the ultimate goal for the survival and profitability of streamer and social media-type platforms (Sun et al., 2019). Consumers expect to receive social benefits and minimise uncertainty in the decision-making process in content-based live streaming commerce. The majority of the previous literature has merely focused on the technical advantage to engage (Liao et al., 2022). A holistic model integrating social factors and technical factors to fully understand live streaming commerce is scant (Ma, 2021a). A similar concern was highlighted by Kim and Kim (2022), who argue that streamer attributes and technical (platform) attributes should be considered together to fully understand user behaviour in live streaming. Corresponding to Ma's (2021a) call, this study adopted the socio-technical theory (Trist et al., 1963) as its underpinning theory by proposing the social factor (i.e., streamer attribute) and technical factor (i.e., technical attribute) that drive purchase intention in live streaming shopping.

An overview of research shows that the socio-technical theory has provided valuable insights into the context of mobile learning (Krotov, 2015), social media (Chai & Kim, 2012; Lee, 2018), sharing commerce (Kong et al., 2020; Tajvidi et al., 2020) and social commerce (Gibreel et al., 2018; Hu et al., 2016). However, research in live streaming commerce remains limited.

In the socio-technical theory, the social subsystem emphasises human-related factors. People are resources to be exploited in the system and are not dispensable (Trist, 1981). Without considering the human factor, the system may cause serious failure (Chai & Kim, 2012). For example, Hu et al. (2016) argue that peer attributes, such as expertise and similarity, are key social subsystem factors that influence purchase intention in social commerce because they allow users to perceive greater utilitarian value and social value. Streamers are the core of live streaming commerce (Kim & Kim, 2022). Unlike traditional e-commerce, where product information is mainly displayed by websites, the content of live streaming commerce is mainly created by streamers (Törhönen et al., 2021). Therefore, this study proposed that streamers attributes are social factors. According to the source credibility model, the spokesperson's expertise and attractiveness are the key factors that influence the effectiveness of the message (Ohanian, 1991). Unlike other business models, live streaming is a tool to build intimacy through real-time communication (Hu et al., 2017; Xu et al., 2020). The communication style of the streamer also plays a key role in predicting consumer behaviour (Fitriani et al., 2020). However, streamers' communication style has received little attention. Hu et al. (2017) have thus suggested that future research should shed light on the impact of the streamer's charm and communication style on consumer behaviour. Therefore, this study takes streamer attributes, including expertise, attractiveness, and interaction orientation, as social factors.

On the other hand, the technical subsystem of the socio-technical theory emphasises processes, tools, and technology (Tajvidi et al., 2020; Trist, 1981). Hu et al. (2016) argue that platforms should provide rich features that transfer information more effectively and personalise recommendations to meet the social and utilitarian needs of social commerce users. Consistent with Hu et al. (2016), media richness and personalisation are considered technical factors for live streaming commerce. Existing research has revealed significant effects of media richness (Chidiac & Bowden, 2023; Liu et al., 2009; Shao & Pan, 2019; Tseng & Wei, 2020). For example, websites with high media richness promote positive consumer behaviour (Marcin Lipowski, 2018; Tseng & Wei, 2020) because vivid displays of media richness allow users to perceive greater diagnosis and enjoyment (Jiang & Benbasat, 2007a; Uhm et al., 2022). In fact, media richness is crucial in the online marketplace because online commerce relies solely on the information provided by the website, which buyers cannot experience or touch, limiting their perception of the product (Chen & Chang, 2018; Chidiac & Bowden, 2023; Tseng et al., 2017). The media richness of the website provides surprisingly wider and deeper senses for customers to recognise the product through various cues (Chen & Chang, 2018). In live streaming commerce, the integration of real-time video, video clips, product images, and textual displays enable consumers to obtain richer and more detailed product information than traditional e-commerce (Liu & Sun, 2023). Therefore, this study proposes that media richness is an effective factor in facilitating users' purchase intention in live streaming commerce.

Moreover, previous studies on online marketing have shown that personalised recommendations can be a fundamental consideration for business success. Studies have shown that personalised recommendations are more likely to be accepted by consumers than non-personalised recommendations (Senecal & Nantel, 2004), leading to more clicks than random recommendations (de Pechpeyrou, 2009) and higher user ratings than random recommendations (Panniello et al., 2017). They also lead to a significant increase in page views/sales and total sales for mobile commerce (Jannach & Hegelich, 2009). This is because personalisation is more self-relevant and content-relevant (Tam & Ho, 2006), making the purchase process more convenient and enjoyable for consumers (Aljukhadar & Senecal, 2011; Xiao et al., 2019). With the assistance of artificial intelligence, machine learning, and big data technology, smart recommendations systems based on user profile and history have become the primary method for users to discover products of interest in live streaming commerce (Sun et al., 2019). Therefore, this study proposes that personalisation can be another technical attribute of live streaming commerce.

In summary, drawing on the socio-technical theory (Trist et al., 1963), this study proposes that streamer attributes (expertise, attractiveness, and interaction orientation) and technical attributes (media richness and personalisation) are drivers of purchase intention in live streaming commerce.

2.11.2 Theoretical Gap 2: Drivers and Consequences of Swift Guanxi

The second theoretical gap aims to examine the drivers and outcomes of swift guanxi. Cultivating swift guanxi with consumers is crucial (Ou et al., 2014a; Sun et al., 2019). A considerable number of marketing scholars have investigated swift guanxi in online marketplaces (Chong et al., 2018) and social commerce (Cheng et al., 2020; Fan et al., 2019; Lin et al., 2017). However, research on the specific characteristics that facilitate swift guanxi and the effect of swift guanxi on purchase intention in live streaming commerce remains limited (Chen et al., 2021; Lin et al., 2019; Sun et al., 2019).

Traditional interpersonal relationships are built on seller' characteristics and relationship behaviours (Palmatier et al., 2006; Verma et al., 2016), such as seller expertise, similarity, and dependence on the seller. However, with the development of online communication technologies, online interpersonal relationships are established through IT mediation. Therefore, technology that can convey richer useable information and which reduce ambiguity is better able to facilitate relationship building (Hsu et al., 2020; Tseng et al., 2017). Consistent with this notion, the socio-technical theory provides a useful framework for identifying interpersonal and technical factors. These interpersonal factors and technical factors as antecedents seem more likely to better facilitate interpersonal relationship formation, such as swift guanxi.

Furthermore, the S-O-R model supports the exploration of antecedents and outcomes of swift guanxi. Specifically, this study proposes that environmental stimuli (streamer attributes and technical attributes) evoke individuals' cognitive reactions (swift guanxi), and the cognitive reaction ultimately leads to a behavioural response (purchase intention) (Mehrabian & Russell, 1974).

2.11.3 Theoretical Gap 3: The Mediating Effect of Swift Guanxi

The third theoretical gap emphasises the mediating mechanism of swift guanxi on purchase intention in live streaming commerce. Most existing research on behavioural intention has only examined the direct relationship between social or technical factors and purchase intention, thus underestimating the overall predictive power. The fact that any technology use model can be enhanced by integrating indirect effects enables practitioners to better understand the mechanisms explaining users' purchase intention. This view is supported by Ou et al. (2014), who argue that consumers who have swift guanxi with sellers are more likely to behave positively. Similarly, Lin et al. (2019) acknowledge that swift guanxi is an important mediator for exploring consumer behaviour.

In this context, the S-O-R model supports the understanding of potential mechanisms in obtaining desired outcomes (Mehrabian & Russell, 1974). Specifically, swift guanxi is an internal cognition that may mediate between the stimuli (streamer attributes and technical attributes) and behavioural outcomes (purchase intention), thus forming the third gap of this study.

2.11.4 Theoretical Gap 4: Influence of Moderating Factors

The fourth theoretical gap in this study highlights boundary conditions (i.e., PEEIM) of swift guanxi in influencing purchase intention. PEEIM is often seen as an important moderator in exploring boundary conditions for relationship effectiveness. Previous research has focused on trust transfer and whether the relationship between trust, satisfaction, and behavioural intention changes under different PEEIM (Bao et al., 2016; Chen et al., 2015; Fang et al., 2014). PEEIM reduces environmental risk by explicitly regulating warranties that are not tied to a specific seller, creating a less risky trading environment. In this environment, buyers who trust the seller are more inclined to develop an intention to purchase from that seller. In contrast, when PEEIM is low, while the relationship with the seller reduces the risk of the seller and the product, risks that are not controllable by the seller, such as privacy issues from the platform, may still hinder the user's purchase intention (Fang et al., 2014).

However, swift guanxi with streamers is different from trust in the vendor or trust in the seller in the context of live streaming commerce (Ou, Pavlou, & Davison, 2014). There is limited research on whether the relationship between swift guanxi (especially swift guanxi between users and streamers) and behavioural intention is moderated by PEEIM (Chen et al., 2022). Ou et al. (2014) also call for future research to consider the effect of both swift guanxi and institutional mechanisms in online markets. To fill this gap, this study provides empirical evidence by introducing the moderating role of PEEIM on the relationship between swift guanxi and purchase intention.

Furthermore, although URT has been widely applied in online social media setting, traditional e-commerce, and social commerce, its application in the live streaming commerce sector has been limited (Antheunis et al., 2010; Gambo & Özad, 2021). To bridge this gap, this study aims to provide empirical evidence by introducing the moderating role of PEEIM, based on URT, into the relationship between swift guanxi and purchase intention.

2.11.5 Contextual Gap

This study also addresses a contextual gap in live streaming commerce. While empirical research on live e-commerce is growing (for example, (Lo et al., 2022; Wongkitrungrueng & Assarut, 2020)), there is still a lack of research focusing on millennial shoppers' expectations when using live e-commerce. To fill this gap, this study centres on millennial consumers' purchase intention in live streaming commerce. This generational cohort will be the biggest challenge for marketing in the future.

Millennials are more self-centred and more willing to consume. Nevertheless, while they are particularly attuned to technological innovation, they are more sceptical than older generations and feel apprehensive and distrustful of the commerce around them. Only designs and services that meet their functional and social needs will win their business (Bilgihan, 2016). Moreover, personalisation and customisation of information and servers are what match their values (Ansari & Mela, 2003; Prasad et al., 2019). Therefore, it is important to investigate the purchase intention of millennial shoppers in live streaming commerce, as researchers and practitioners believe that their behaviour reflects the way people will behave in the future.

Furthermore, China is still a developing country with the highest Internet penetration rate. China's e-commerce live streaming is also in the leading position worldwide (MOF, 2021). Compared with other countries, the development of e-commerce live streaming in China has unique characteristics (CC-Smart, 2020). Moreover, China is a multi-racial country with stable economic growth prospects and is the commercial centre for many local and international companies to develop their business. For example, many international brands and retailers, such as L'Oreal, Ikea, and Uniqlo, have used live streaming commerce to expand their online marketing. With countless business opportunities and a huge population from diverse backgrounds, China is an ideal environment to explore. Thus, the study of live streaming commerce in China has a huge impact on streamers, brands, social media platforms, the economy, and the country.

2.12 Chapter Summary

This study outlines four noteworthy theoretical gaps in the context of live streaming commerce. First, there is a lack of influence on the linked role of social and technical factors on purchase intention in live streaming commerce. Studies have shown that both streamer attributes and technical attributes have significant effects on live streaming commerce streaming (e.g., Guo et al., 2022; Sun et al., 2019). The socio-technical theory (Trist et al., 1963) argues that the social subsystem and technical subsystem should work together to achieve the best performance of a system (Bostrom & Heinen, 1977). Hence, this study proposes streamer attributes and technical attributes as social and technical factors that directly impact the purchase intention of live streaming commerce. Second, swift guanxi is an interpersonal seller-consumer relationship in the Chinese context. This study further proposes that its formation depends on streamer attributes and technical attributes. Third, swift guanxi is an important mechanism of purchase intention, as supported by the S-O-R model (Mehrabian & Russell, 1974). It contributes extensively to the understanding of purchase intention in live streaming commerce. Lastly, relatively few research has investigated the boundary conditions of purchase intention in live streaming commerce. In this case, PEEIM are incorporated as boundary conditions to explore the effectiveness of swift guanxi on purchase intention. Overall, this study takes concrete steps to address four theoretical gaps in the literature by developing a comprehensive model.

CHAPTER 3

RESEARCH FRAMEWORKS AND HYPOTHESIS DEVELOPMENT

3.1 Introduction

This chapter presents the arguments for the proposed hypothesis. First, the research framework for this study is presented. The subsequent section focuses on the development of the direct hypotheses. Then, the rationale for mediating and moderating effects is provided. Finally, the chapter concludes with a set of hypotheses.

3.2 Conceptual Framework

Based on the research gap identified in Chapter 2, along with the socio-technical theory proposed by Trist et al. (1963), the S-O-R model proposed by Mehrabian and Russell (1974), and the uncertainty reduction theory proposed by Berger and Calabrses (1975), this study proposes a research framework for investigating the purchase intention of millennial live streaming commerce users.

First, supported by socio-technical theory, the study proposes that streamer attributes and technical attributes influence the purchase intention of live streaming commerce users (see Figure 3.1). Specifically, streamer attributes include expertise, attractiveness, and interaction orientation, while technical attributes encompass media richness and personalisation.

Next, the S-O-R model (Mehrabian & Russell, 1974) was used as a supporting theory to explain the mediating role of swift guanxi (organism) on the effect of streamer attribute and technical attribute on purchase intention (see Figure 3.1). In this study, swift guanxi was operationalised through three lower-order components: mutual understanding, reciprocal favours, and relationship harmony.

Finally, supported by URT, this study hypothesises that PEEIM may moderate the path between swift guanxi and purchase intention (see Figure 3.1). As shown in Figure 3.2, this study includes seventeen hypotheses, with hypotheses H1-H3 focusing on direct effects, hypotheses H4a-H4e focusing on mediating effects, and H5 focusing on moderating effects. The rationale for each hypothesis is presented in Sections 3.5 to 3.11.

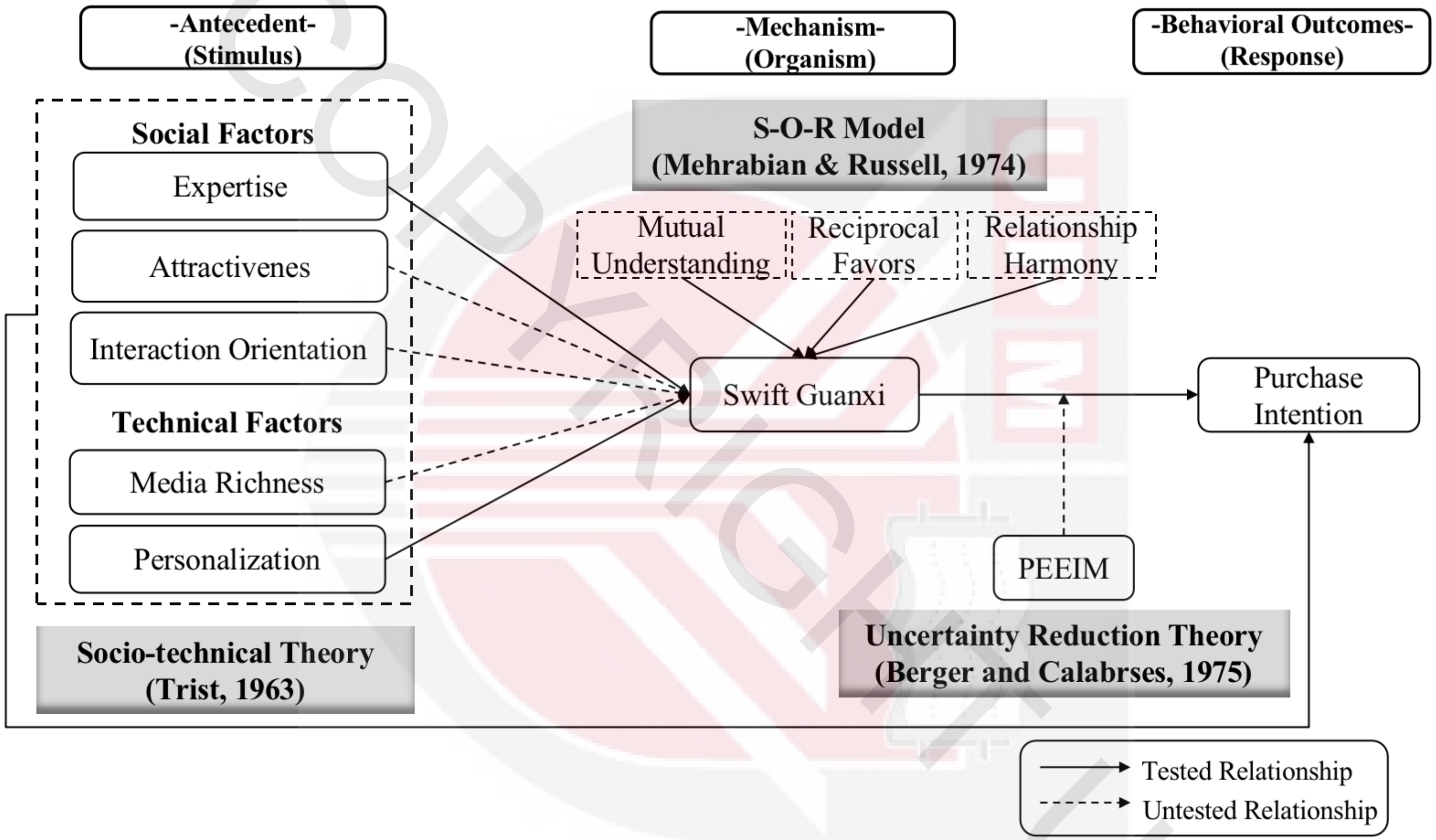

Figure 3.1 : Theoretical Framework

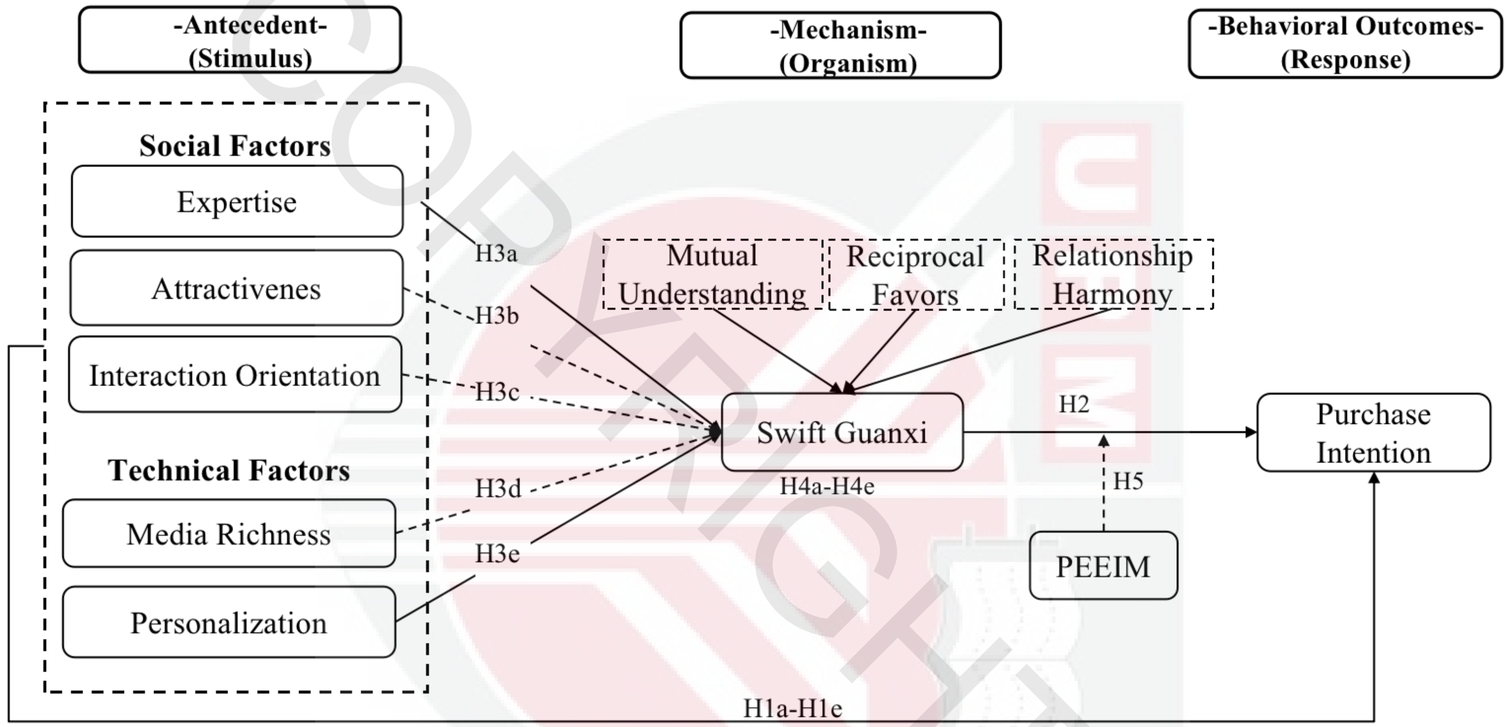

Figure 3.2 : Proposed Framework

3.3 Streamer Attributes and Purchase Intention

According to socio-technical theory, social factors play a key role in influencing positive behavioural intentions (Bostrom & Heinen, 1977; Trist et al., 1963). Early research by Lin et al. (2008) on virtual communities demonstrate that social factors are critical for implementing thriving communities. This perspective is supported by Chen and Qi (2015), who found that social factors, including social interaction ties, trust, reciprocity, and shared vision, can enhance users' satisfaction and consequently leads to a greater willingness to purchase. A study conducted by Hu et al. (2016) suggested that social factors are the main drivers that influence users' purchase intention in social commerce (Hu et al., 2016). These research confirm the idea that people are resources to be leveraged rather than dispensable when predicting positive purchase intentions.

As the content creators and core of live streaming commerce, streamer attributes are the key factors that drive the success of the system. In other words, it is reasonable that when streamers are perceived as credible, users are more likely to purchase. Based on the source credibility model (Ohanian, 1990) and previous literature review, expertise, attractiveness, and interaction orientation are the three main dimensions of streamer credibility. Moreover, previous studies further show that the influencer's credibility positively impacts the effectiveness of advertisements and users' purchase intention (Amos et al., 2015; Weismueller et al., 2020).

In live streaming commerce, expertise refers to streamers' knowledge, experience, qualifications, and achievements in broadcasting or selling related products (Guo et al., 2022). According to the source credibility model, users are more willing to interact with professional streamers and believe their content is more credible and convincing (Hovland et al., 1953). In addition, the accumulation of product expertise allows streamers to recommend the most suitable products and more useful information for consumers, which can significantly reduce consumers' efforts in product search, evaluation, and decision-making (Hu et al., 2016) and uncertainty about products (Ismagilova et al., 2020). According to the socio-technical theory (Trist et al., 1963), the expertise of the streamer is considered a social factor whose absence may cause the termination of the purchase. In other words, the presence of streamer expertise may lead to purchase intention. Therefore, this study proposes that the expertise of the streamer positively influences users' purchase intention.

Secondly, physical attractiveness refers to the degree to which a streamer has an attractive and pleasing physical appearance (Ahearne et al., 1999). According to the halo effect and congruency theory, physically attractive people are perceived to be more approachable, interesting, competent, and credible (Ahearne et al., 1999; Till & Busler, 2000). Furthermore, a positive attitude toward the communicator implies a more positive evaluation of the message (Joseph, 1982) and an easier agreement (Horai et al., 1974). Previous literature acknowledged that consumers showed higher purchase intentions when they interact with attractive salespeople (Ahearne et al., 1999). Research has also shown that consumers are more likely to form a para-social relationship with an attractive spokesperson to increase purchase intention (Gong & Li, 2017). An additional fact is that attractive spokespeople are perceived to be more credible than unattractive spokespeople, which triggers consumers' desire to purchase (Sokolova & Kefi, 2022). Due to the visibility of the live streaming, the face, voice, and body of the streamer can be recognised by the viewer. Therefore, it is reasonable to infer that consumers can generate positive purchase intentions in streaming commerce when the streamer is physically attractive.

Lastly, interaction orientation is a customer-centred communication style that focuses on meeting the needs of the customer through a more intense and authentic dialogue between the salesperson and the customer (Wirtz et al., 2010). Previous research has found that the impact of interaction-orientation on desired outcomes depends on the complexity and importance of the buying situation. For the most part, interaction-orientation is effective in enhancing persuasion, trust, satisfaction, and patronage intentions (Homburg et al., 2011; M. Li & Ma, 2022; Williams & Spiro, 1985). Keeling et al.'s (2010) study reveals the same idea where interaction-oriented avatar proactively interacts with and helps users, and its "friendly" and "helpful" behaviour significantly enhances users' trust and patronise intention (Keeling et al., 2010). Likewise, Bateman and Valentine's (2015) study found that salesperson interaction orientation leads to an improved assessment of salesperson ethics toward customers and stronger purchase intention (Bateman & Valentine, 2015). Thus, in the context of live streaming commerce, the interaction-oriented communication of streamers is an important factor driving users' willingness to purchase.

According to the socio-technical theory (Trist et al., 1963), the streamer's expertise, attractiveness, authenticity, and interaction orientation are considered to be social factors whose absence may cause the termination of purchase. In other words, the presence of the streamer's expertise, attractiveness, and interaction orientation may lead to purchase intention. Thus, streamer expertise, attractiveness and interaction orientation may lead to the purchase intention of millennials in live streaming commerce. Therefore, this study formulated the following hypothesis:

H1a: Streamer expertise is positively related to purchase intention among millennial live streaming shoppers in China.

H1b: Streamer attractiveness is positively related to purchase intention among millennial live streaming shoppers in China.

H1c: Streamer interaction-oriented communication style is positively related to purchase intention among millennial live streaming shoppers in China.

3.4 Technical Attributes and Purchase Intention

Based on the socio-technical theory, technical attributes are another key factor driving the success of information systems (Bostrom & Heinen, 1977; Trist et al., 1963). A study by He dehua et al. (2008) found that a website's ease of use and usefulness can significantly affect user's attitude and encourage purchasing intentions in online C2C markets. Additionally, Hu et al. (2016) highlighted that technical factors primarily drive social commerce users' buying intentions. Specifically, enhanced technical features increase users' perceived value, leading to a rise in purchase intentions. Overall, technical features form the foundational functions that facilitate positive purchasing intentions.

Previous studies have also shown that platforms that deliver useful information more effectively can improve users' perceptions of information quality (Ma, 2021a) and value perception (Hu et al., 2016). Based on previous literature reviews, media richness and personalisation are two main technical attributes of live streaming commerce.

Firstly, media richness, as a technical characteristic of live streaming commerce, refers to the ability of multiple cues of products to be conveyed (Brunelle, 2009; Daft & Lengel, 1986). According to cue summation theory, more cue stimuli promote more effective consumer learning (Severin, 1967). Previous literature has emphasised that product displays with high media richness promote consumers' purchase intention compared to pale product demonstrations because vivid product displays generate more emotional appeal (Jiang & Benbasat, 2007a). The broad and deeper sensory information from media richness is more likely to capture and hold the user's attention and stimulate the imagination (Yim et al., 2017). In addition, according to Sundar's MAIN model (2008), the form in which information is presented affects users' judgments of the credibility of the information. Several studies have shown similar assertions that platforms with high media richness can enable recipients to better understand the product and improve users' perceptions of usefulness, credibility, and persuasiveness when processing information (Jiang & Benbasat, 2007a; Tang, 2012). Therefore, this study proposed that media richness increases consumers' purchase intention in live streaming commerce.

Personalisation aims to maximise immediate and future business opportunities by using personalisation techniques to deliver the right information in the right format to the right person at the right time (Tam & Ho, 2006). Previous studies have shown that personalisation plays an important role in influencing consumer decisions (Tam & Ho, 2005, 2006). Aljukhadar and Senecal (2011) suggested that personalised recommendations aligned with consumer needs can shorten consumers' shopping durations and enhance the convenience and enjoyment of the shopping journey. In online marketing, personalised messages are often more effective than non-personalised messages, such as being more likely to be remembered and liked (Li, 2016; Liu et al., 2021; Pappas et al., 2014). Also, in the realm of mobile commerce, such recommendations result in a notable surge in both page views and sales (Jannach & Hegelich, 2009). In live streaming commerce, data-driven personalisation provides products and information that better match user needs, mitigates search effort and transaction time, and increases satisfaction. Therefore, it is reasonable to infer that personalisation can increase users' purchase intention in live streaming commerce.

Consistent with the socio-technical theory (Trist et al., 1963) that technical attributes are important factors for the success of system, this study hypothesises that media richness and personalisation are the driving factors that encourage the purchase intention of live streaming commerce users. Therefore, the hypothesis was formulated as:

H1d: ***Media richness is positively related to purchase intention among millennial live streaming shoppers in China.***

H1e: ***Personalisation is positively related to purchase intention among millennial live streaming shoppers in China.***

3.5 Swift Guanxi and Purchase Intention

Swift guanxi is defined as "a quickly formed reciprocal-based interpersonal relationship between buyer and seller" in the Chinese cultural context (Ou, Pavlou, & Davison, 2014). As suggested by Ou et al (2014), this term refers to a multidimensional construct that includes three dimensions: mutual understanding, reciprocal favours, and relationship harmony (Ou, Pavlou, & Davison, 2014).

Swift guanxi has been consistently reported to have a significant positive impact on consumer behaviour. Consumers who have swift guanxi with a seller/host are more likely to exhibit satisfying behaviours such as engagement (Guo et al., 2021), stronger word-of-mouth recommendations (Bilal et al., 2022; Shi et al., 2018) and loyalty (Tseng et al., 2022). Previous research also suggests that when consumers form swift guanxi with peer users, eWOM behaviour and eWOM adoption behaviour can increase directly (Cheng et al., 2020). Another study conducted by Lin et al. (2018) also revealed that patronage behaviour and positive share intention are the results of swift guanxi.

As an online extension of the traditional guanxi, the key role of swift guanxi for purchase intention and repurchase intention has been widely validated in various fields, including e-commerce (Chiu et al., 2018; Niu et al., 2020; Ou, Pavlou, & Davison, 2014; Shi et al., 2018). Consumers who have a swift guanxi with a seller or website are more likely to show repeat purchases (Fan et al., 2019; Shang & Bao, 2022). Similar results were found in a study by Zhang et al. (2020), which highlighted that consumers who form swift guanxi with a website or seller are more willing to purchase products from the company. Therefore, establishing swift guanxi with consumers is crucial because mutual understanding, reciprocity, and harmonious relationships between consumers and sellers reduce consumer uncertainty (Chiu et al., 2018) and ensure a smooth transaction, which benefits both parties (Ou, Pavlou, & Davison, 2014).

The S-O-R model proposes that an "organism" has a positive impact on a "response" behaviour. Based on this, it can be concluded that swift guanxi is a driver of purchase intention for live streaming commerce users. It is hypothesised that millennial shoppers who form swift guanxi with streamers are likely to make purchases on live e-commerce platforms. Therefore, this study hypothesises that:

H2: ***Swift guanxi with streamers is positively related to purchase intention among millennial live streaming shoppers in China.***

3.6 Streamer Attribute and Swift Guanxi

Expertise refers to a person's level of domain-specific knowledge (Shen et al., 2010). A higher level of expertise implies that the streamer can provide more structured information and offer better evaluations of the product. This reduces information asymmetry and enhances mutual understanding between the streamer and the audience (Hu et al., 2016). Furthermore, according to social exchange theory, when customers interact with professional salespeople who are perceived as reliable, knowledgeable, and responsive, they receive more value, and in return, the quality of their relationship with the salesperson becomes stronger (Crosby et al., 1990; Guenzi & Georges, 2010; Ladhari et al., 2020). Also, previous research has shown that smooth interactions can lead to harmonious relationships (Tseng et al., 2022). In live streaming commerce, users can ask questions about products through pop-ups. Streamers with expertise know more about the product's features and can better personalise their answers to pop-up questions, which makes for a harmonious relationship. Therefore, it is believed that the expertise of streamers will support the formation of swift guanxi in live streaming commerce.

Previous studies have asserted that attractiveness is an essential factor in building relationships (Ladhari et al., 2020). In support of this notion, Sokolova and Kefi (2022) claim that individuals prefer to interact with attractive people and perceive them as sociable. Intense interactions are necessary for mutual understanding because users can communicate product details and prices (Fan et al., 2019; Shang & Bao, 2022). Similarly, the feeling of mutual understanding creates an atmosphere in which both parties can reciprocate (Ou, Pavlou, & Davison, 2014). Furthermore, people have the “Beautiful is Good” stereotype. Physically attractive people are perceived as more warm and more trustworthy (Dion et al., 1972). In other words, interaction with attractive people is seen as a positive experience that makes people more pleasant and aroused (Ahearne et al., 1999; Hou, Guan, et al., 2020). In this positive atmosphere, people are more likely to reach harmony and consensus in relationships. In live streaming commerce, the physical attractiveness of the streamer determines the viewer's first impression of the streamer, and it brings positive emotions as well as an emotional connection to the viewer (Chaker et al., 2019). Thus, compared to streamers with low attractiveness, buyers are more likely to develop swift guanxi with attractive streamers.

Interaction orientation is a communication style that emphasises active, friendliness, empathy, and helpfulness, with the main goal of forming interpersonal relationships (Williams & Spiro, 1985). Interaction-oriented streamers actively interact with users, and their helpful behaviour promotes a better understanding of the product for users (Fitriani et al., 2020). Besides, according to social exchange theory, the support of one party provides social benefits and, therefore, instils a reciprocal obligation (Tseng et al., 2022). Similarly, the helping behaviour of streamers makes users expect a reciprocal return, thus reaching reciprocal favour in the relationship. Furthermore, existing research has shown that when interaction-oriented streamers deliver information in a friendly and empathetic manner, it leads to a stronger sense of comfort among users (Li & Ma, 2022; Williams & Spiro, 1985). In this case, they are more likely to reach harmony and consensus in the relationship (Ou, Pavlou, & Davison, 2014). Thus, in the context of live streaming commerce, interaction-oriented communication by streamers is positively related to swift guanxi.

In line with the S-O-R model, streamers are considered to be stimuli that positively influence the cognitive state (i.e., organism) of consumers. Therefore, positive streamer attributes are expected to enhance swift guanxi. Thus, this study proposes the following hypotheses:

H3a: ***Streamer expertise is positively related to swift guanxi among millennial live streaming shoppers in China.***

H3b: ***Streamer attractiveness is positively related to swift guanxi among millennial live streaming shoppers in China.***

H3c: ***Streamer interaction-oriented communication style is positively related to swift guanxi among millennial live streaming shoppers in China.***

3.7 Technical Attribute and Swift Guanxi

Media richness conveys deeper sensory and non-sensory information, which is particularly important in situations of uncertainty and ambiguity (Daft & Lengel, 1986; Shao & Pan, 2019). By mitigating information asymmetry, users and streamers can more easily reach mutual understanding (Lin et al., 2019). Secondly, harmonious relationships are more likely to be formed in a friendly and sociable environment (Ou, Pavlou, & Davison, 2014). Media richness not only conveys product information, but also vividly conveys the streamer's voice, posture and product introduction, giving users a warm and pleasant feeling of being together (Sun et al., 2019). Similarly, mutual understanding and warm feelings create an atmosphere where users and streamers can reciprocate (Ou, Pavlou, & Davison, 2014). If users receive limited cues, then they are less likely to build mutual understanding, reciprocity, and harmonious guanxi. Thus, this study proposes that media richness is positively related to users' purchase intentions.

Previous research has shown that personalised recommendations are one of the most successful relationship building strategies used by online commerce companies (Wirtz et al., 2010). For example, Komiak and Benbasat (2006) clarifies that personalised recommendations enable users to perceive the care and empathy of a website, thereby increasing customer trust and adoption of recommendations. When customers find personalised recommendations in a medium, they develop a stronger sense of social identity and familiarity with the recommended streamers in the channel because recommendations from the platform are perceived as more credible (Kumar & Benbasat, 2006). In addition, previous research has shown that swift guanxi is formed through interactions between two parties (Chong et al., 2018; Ou et al., 2014). Personalised recommendations facilitate interpersonal and product interactions between users, and as a result, warm and close relationships are induced (Kumar & Benbasat, 2006). Based on these findings, this study proposes that personalisation is positively related to swift guanxi in live streaming commerce.

Therefore, with the support of the S-O-R model, the following hypothesis was proposed:

***H3d:* *Media richness is positively related to swift guanxi* among millennial live streaming shoppers in China.**

H3e: Personalisation is positively related to swift guanxi among millennial live streaming shoppers in China.

3.8 Mediating Role of Swift Guanxi

The S-O-R model provides a conceptual basis for the mediating role of swift guanxi in shaping purchase intention in live streaming commerce. In this model, Mehrabian and Russell (1974) defines the "organism" as the cognitive and emotional state within an individual. Specifically, the organism plays a mediating role in linking stimuli to responses. In this study, swift guanxi is identified as a critical organism.

Based on previous research findings, the relationship between swift guanxi and behavioural intentions is evident. Consumers who have swift guanxi with a seller or website are more likely to exhibit positive behaviours such as sharing and purchasing (Chiu et al., 2018; Fan et al., 2019; Lin et al., 2017; Niu et al., 2020; Ou, Pavlou, & Davison, 2014; Shang & Bao, 2022; Shi et al., 2018). Similarly, studies have highlighted that swift guanxi occurs through cues embedded in virtual environments and will in turn promote optimal consumer behaviour (Chen et al., 2021; Lin et al., 2017). Another study by Zhang et al. (2020) found that an individual's online purchase behaviour is highly associated with his/her her interpersonal relationship with the seller. In addition, various consumer behaviour studies have shown that swift guanxi is a key mediating variable in the path of consumer purchase behaviour (Chen et al., 2021; Shi et al., 2018). In live streaming commerce, expertise, attractiveness, and interaction orientated streamers who actively provide assistance are more likely to form a mutually understanding, reciprocal, and harmonious relationship. Meanwhile, communication is mediated through IT, so platforms that provide more media-rich communication channels and personalised recommendations are more likely to facilitate the development of swift guanxi between streamers and users. In turn, this mutual understanding, reciprocal and harmonious relationship guarantees smooth transactions (Chiu et al., 2018; Fan et al., 2019; Lin et al., 2017; Niu et al., 2020; Ou, Pavlou, & Davison, 2014; Shang & Bao, 2022; Shi et al., 2018).

Based on this principle, swift guanxi is considered as the mechanism that links live streaming commerce stimuli (i.e., streamer attributes and technical attributes) to purchase intention. Accordingly, this study proposes the following hypotheses:

H4a: Swift guanxi mediates the relationship between expertise and purchase intention among millennial live streaming shoppers in China.

H4b: Swift guanxi mediates the relationship between attractiveness and purchase intention among millennial live streaming shoppers in China.

H4c: Swift guanxi mediates the relationship between interaction orientation and purchase intention among millennial live streaming shoppers in China.

H4d: Swift guanxi mediates the relationship between media richness and purchase intention among millennial live streaming shoppers in China.

H4e: Swift guanxi mediates the relationship between personalisation and purchase intention among millennial live streaming shoppers in China.

3.9 Moderating Role of PEEIM

The present study proposes that the effect of swift guanxi on purchase intention is not the same for live streaming commerce shoppers. This is because it may be influenced by PEEIM, which refers to buyers believing that there is an institutional safeguard in the online marketplace to protect them from potential risks, including third-party assurance mechanisms, escrow services, and privacy protection (Fang et al., 2014).

Although guanxi stems from the opacity and inadequacy of legal mechanisms in the Chinese context, as the legal system gradually improves, Chinese people still tend to form guanxi to conduct transactions, either offline (Ambler et al., 1999; Arias, 1998) or online (Hsiao, 2003; Martinsons, 2008). The ability of swift guanxi to enhance transactions lies in their capacity to reduce uncertainty linked to streamers and products (Chiu et al., 2018). In other words, swift guanxi empowers customers to subjectively eliminate potential negative behaviours from streamers, consequently reducing the perceived risk to a more manageable level. As a result, swift guanxi is regarded as an essential indicator for online purchase behaviour (Fan et al., 2019; Lin et al., 2019).

In the context of live streaming shopping, PEEIM can mitigate customers' awareness of inherent environmental risks within the general s-commerce landscape—risks that are independent of the streamers (Fang et al., 2014). For instance, issues related to the security of the public internet infrastructure may lead online customers to experience losses due to credit card fraud or privacy breaches (Fang et al., 2014). Previous research has shown that if buyers have high PEEIM, they perceive less context risk and are more willing to exchange information or emotional interactions to achieve further mutual understanding, thus facilitating the formation of a strong tie (Dong & Wang, 2018). This strong tie leads users to purchase from the seller (Chen et al., 2015). Similarly, Chen et al. (2022) further verified in a social commerce context that high levels of PEEIM can reduce buyers' uncertainty about the transaction and thus contribute to swift guanxi more effectively in reducing perceived uncertainty (Chen, Wang, et al., 2022). Similarly, in live streaming commerce, when buyers have high PEEIM, buyers who have swift guanxi with the streamer are more willing to form a positive purchase intention with this streamer. Accordingly, this study proposes the following hypothesis:

H6: PEEIM positively moderates the relationship between swift guanxi and purchase intention, where the relationship is stronger when PEEIM is high.

3.10 Overall Proposed Hypotheses

Based on the justifications provided in earlier sections, seventeen hypotheses were proposed in the present study. The list of hypotheses statements is presented in Table 3.1.

Table 3.1 : List of Hypothesis Statements

Num	Path	Hypothesis Statement
1	H1a	Expertise is positively related to purchase intention among millennial live streaming shoppers in China.
2	H1b	Attractiveness is positively related to purchase intention among millennial live streaming shoppers in China.
3	H1c	Interaction orientation is positively related to purchase intention among millennial live streaming shoppers in China.
4	H1d	Media richness is positively related to purchase intention among millennial live streaming shoppers in China.
5	H1e	Personalisation is positively related to purchase intention among millennial live streaming shoppers in China.
6	H2	Swift guanxi is positively related to purchase intention among millennial live streaming shoppers in China.
7	H3a	Expertise is positively related to swift guanxi in live streaming shopping among millennial shoppers.
8	H3b	Attractiveness is positively related to swift guanxi among millennial live streaming shoppers in China.
9	H3c	Interaction orientation is positively related to swift guanxi among millennial live streaming shoppers in China.
10	H3d	Media richness is positively related to swift guanxi among millennial live streaming shoppers in China.
11	H3e	Personalisation is positively related to swift guanxi among millennial live streaming shoppers in China.
12	H4a	Swift guanxi mediates the relationship between expertise and purchase intention among millennial live streaming shoppers in China.
13	H4b	Swift guanxi mediates the relationship between attractiveness and purchase intention among millennial live streaming shoppers in China.
14	H4c	Swift guanxi mediates the relationship between interaction orientation and purchase intention among millennial live streaming shoppers in China.
15	H4d	Swift guanxi mediates the relationship between media richness and purchase intention among millennial live streaming shoppers in China.
16	H4e	Swift guanxi mediates the relationship between personalisation and purchase intention among millennial live streaming shoppers in China.
17	H5	PEEIM positively moderates the relationship between swift guanxi and purchase intention in live streaming shopping, where the relationship is stronger when PEEIM is high among millennial shoppers.

3.11 Summary

This chapter discussed the conceptual framework and hypotheses of this study. The theoretical framework is underpinned by the socio-technical theory (Trist et al., 1963), which investigates the drivers of purchase intention for live e-commerce for Chinese millennial mobile shoppers. Based on socio-technical theory (Trist et al., 1963), streamer attribute and technical attribute are included as social and technical factors that enhance purchase intention. This study also explored the mediating effect of swift guanxi between antecedent and outcome variables supported by Mehrabian and Russell's (1974) S-O-R model. Finally, this study explores the moderating effect of PEEIM on the relationship between swift guanxi and purchase intention. In total, 17 hypotheses were formulated. The subsequent chapter will elaborate on the research methodology.

CHAPTER 4

METHODOLOGY

4.1 Introduction

This chapter begins by discussing the research paradigm and research design that met the objectives of this study. Then, the population of the study, sample size, sampling technique, and the data collection method are discussed. The chapter continues with an explanation of the research instruments and the procedures for pre-test and pilot test prior to collecting the actual data, including their validity and reliability. Finally, the data analysis method is explained.

4.2 Research Paradigm

A research paradigm is the basic orientation of theory and research (Saunders et al., 2019). It represents the standpoint from which researchers conduct their research and their general philosophical orientation toward the world (Creswell, 2014). The research paradigm consists of two main dimensions that shape the entire research process: ontology (concerned with the nature of reality) and epistemology (focused on what can be known) (Saunders et al., 2019). In essence, a research paradigm is a guiding way of thinking that influences a researcher's choices in terms of the questions to ask, procedures to employ, types of data to gather, and strategies for data interpretation. The two most prevalent research paradigms in social science are positivism and interpretivism (McChesney & Aldridge, 2019).

Positivism believes that reality is stable and can be observed and characterised objectively, resulting in law-like generalisations (Saunders et al., 2019). Ontologically, positivists consider that organisations and other social things, like physical objects and natural events, are real and objectively exist (Saunders et al., 2019). Epistemology is also objective, emphasising cause-and-effect relationships. This paradigm is theory-driven and employs deductive logic to support the object of study (Bougie & Sekaran, 2013). Positivism uses a measurable and systematic approach to obtain results and explains a phenomenon quantitatively.

Interpretivism emerged as a critique of positivism, asserting that positivism is inadequate in addressing the subtleties and variations in human interaction (Saunders et al., 2019). Ontologically, interpretivists argue that there are multiple realities, and that reality is constructed. They believe that there is no objective knowledge independent of human thought and reasoning. Thus, knowledge is an act of interpretation (Saunders et al., 2019). Consequently, they attempt to understand phenomena from a subjective standpoint. Interpretivist research seeks to generate fresh and deeper insights and interpretations of social environments and contexts. They engage closely with participants to foster mutual understanding. In contrast to positivism, the constructivist paradigm aims to evaluate and refine theories (Saunders et al., 2019). Interpretivism research is value-bound, and researchers actively participate in the data collection process by interacting with respondents to yield more meaningful results (Neuman & Kreuger, 2003). Due to this, interpretivism typically requires a qualitative research design that utilises individual interviews and focus group discussions to gather data (Crotty, 1998).

This study adopts a positivist paradigm based on the research objectives presented in Chapter One. As previously noted, positivism focuses on theory testing (Creswell, 2014). Consistent with this, this study proposes the socio-technical theory as the underpinning theory, upon which hypotheses are formulated to test the determinants of Chinese consumers' purchase intention in live streaming commerce. The positivist approach is used to collect empirical data from a target sample and follow a quantitative research design for objective reasoning (Creswell, 2014; Phillips et al., 2000).

4.3 Research Design

A research design is a plan or roadmap that outlines how, when, and where data will be collected and analysed to answer a research question or test a research hypothesis (Polit & Beck, 2010). The goal of the research, whether it involves testing, discovering, or developing theory, influences the choice of an effective research design (Gill & Johnson, 2010). In social science, there are two fundamental types of research designs: quantitative and qualitative (Creswell, 2014). The quantitative research design is rooted in positivism and can be seen as a data concentrator, condensing information to infer the whole (Neuman & Robson, 2014). In contrast, the qualitative research design is grounded in the constructivist paradigm (Creswell, 2014). Qualitative research can be seen as a data enhancer, allowing researchers to enrich data to acquire a deeper understanding (Neuman & Robson, 2014).

Based on the positivist paradigm, a quantitative research design was used in this study. Quantitative research aims to describe how a phenomenon occurs through theory testing (Creswell, 2014). Thus, it is commonly connected with deductive reasoning, involving the collection and analysis of data to evaluate hypotheses. The researcher initially outlines the relationships between the constructs and then tests the theoretical relationships using empirical evidence (Saunders et al., 2019). In other words, quantitative research allows the researcher to explain and test hypothesised relationships through statistical methods (Bougie & Sekaran, 2013). The main objective of this study is to examine the relationships between the variables in the proposed research framework. This objective is consistent with the quantitative research design. Therefore, this study adopted a quantitative research design to understand the drivers of purchase intentions among Chinese millennial consumers in live streaming commerce.

In quantitative research, surveys and experiments are two of the most widely used approaches in marketing research (Saunders et al., 2019). However, experimental research can create situations that are not realistic. The variables of a product, theory, or idea are under such tight controls that the data being produced can be corrupted or inaccurate, but still seem like it is authentic (Saunders et al., 2019). This can work in two negative ways for the researcher. First, the variables can be controlled in such a way that it skews the data toward a favorable or desired result. Second, the data can be corrupted to seem like it is positive, but because the real-life environment is so different from the controlled environment, the positive results could never be achieved outside of the experimental research (Saunders et al., 2019). This is particularly true in the context of live streaming commerce, where users may encounter countless variations in stimulus exposure during the shopping experience, potentially rendering any experimental design inconclusive. Furthermore, some people are reluctant to participate in experiments, so such volunteers may not be representative of the entire population (Saunders et al., 2019). Therefore, experimental strategies are often only used for specific groups of people, such as college students and employees of specific organisations (Saunders et al., 2019). Meanwhile, this study focuses on live streaming commerce users. Therefore, the experimental design may result in atypicality, which may lead to problems of external validity (Saunders et al., 2019). In comparison, the survey design enables researchers to administer a questionnaire to a small group of individuals (called a sample) to elucidate trends in the attitudes, thoughts, actions, or characteristics of a larger group of individuals (called a population) (Creswell, 2014). One of the strengths of this approach is that researchers can carefully select and filter participants, ensuring that the sample accurately reflects the population pertinent to the study and provides useful details for drawing conclusions (Marsden & Wright, 2010; Summers, 2001). Therefore, this study distributed online questionnaires to the target respondents (i.e., millennial live commerce shoppers) and analysed the quantitative data through a series of statistical analyses. The data collection process is discussed in Section 4.7.

Overall, the research methodology of this study is based on quantitative approaches, incorporating a survey strategy and collecting data through online questionnaires. The temporal period is cross-sectional since the majority of data is collected at a single moment in time (Malhotra et al., 2017; Saunders et al., 2019).

4.4 Population of Study

Population refers to all individuals or objects that conform to a list of terms and conditions in agreement with the purpose of the study under investigation (Hair et al., 2018). The population of this study is Chinese millennials who are live streaming commerce shoppers on content sharing platforms.

This study investigates live streaming commerce on content sharing platforms, specifically focusing on the platforms Douyin, Kuaishou, and Xiaohongshu. These three leading content sharing platforms boast monthly active user counts of 680 million, 390 million, and 200 million, respectively, with average daily usage times of 108 minutes, 102 minutes, and 66 minutes (Chanmama, 2022). Content-sharing platforms are reshaping the live commerce market due to their extensive user base and user stickiness (Lu & Chen, 2021). Thus, delving into live streaming commerce on content platforms can offer valuable insights to both scholars and practitioners.

In addition, there are several reasons for investigating millennials' willingness to purchase in live streaming commerce. Millennials account for more than 75% of live streaming commerce users, making up the largest share (iiMedia, 2024). Besides that, 66.2% of users had shopped at least once via live streaming commerce, and 17.8% of users have shopping experience in live streaming platforms that account for more than 30% of their total online shopping consumption (CNNIC, 2021). Compared to other demographic groups, millennials are more demanding and sophisticated when shopping online, viewing the experience as a form of entertainment (KHAN & M, 2019). They are also the age group that businesses need to focus on the most to gain profits due to their substantial disposable income (Khoros, 2020). Moreover, millennials have become the mainstay of current consumption and represent an important customer segment that marketers should not ignore. Instead, they must be actively reached and managed, particularly in the realm of virtual sales (Ladhari et al., 2020; Soares et al., 2017). Therefore, understanding their behaviour can provide useful information for scholars and practitioners.

4.5 Sample Size

A sample represents a subset of the population of the study. A good sample can reflect the characteristics of the population so that researchers can draw meaningful conclusions about the population. Different research models and methods of analysis require different sample sizes (Hair et al., 2018). It is widely reported that larger sample sizes tend to yield more reliable results. However, collecting data from large samples also leads to risks in terms of research economics and time. Therefore, determining the final sample size often involves balancing various factors such as time, budget, and the necessity for accuracy (Hair et al., 2018).

Previous scholars have emphasised several factors to consider when deciding on sample size, including the complexity of the research model, expected missing or unusable data, and data collection procedures (Hair et al., 2016). In fact, some researchers believe that sample sizes greater than 200 are sufficient to improve the accuracy of unknown parameter estimates (Hair et al., 2018). An alternative method for determining the minimum sample size is known as the ten-fold rule. This principle suggests that the sample size ought to be ten times larger than the maximum count of arrows pointing to a particular construct (Hair et al., 2016). According to this rule, 80 complete responses is needed for this study ($8 \times 10 = 80$). Nonetheless, these recommendations have also been criticised for inaccurate estimates, especially when the research model is very complex (Goodhue et al., 2012).

Another widely accepted method for determining the sample size is power analysis. The power (1- β) refers to the probability of obtaining a statistically significant result for the alternative hypothesis (H_1) by correctly rejecting the null hypothesis (H_0)

(Cohen, 1988). Before commencing a study, an a priori power analysis can be conducted to establish the sample size based on α, power, and effect size (Cohen, 1988, 1992). According to guidelines, the minimum study power is 0.80, and the effect size is 0.15 (Faul et al., 2007).

G*Power 3.1 software by Faul et al. (2007) was used to calculate the sample size for this research. With an effect size of 0.15, marginal error of 5%, power of 0.95, and eight (8) predictors, the power analysis results suggested that the minimum sample size that should be considered was 160 respondents. Table 4.1 illustrates a correlation between the sample size and the overall model's power. From this, this study can infer that a sufficient sample size is essential for testing the large and complex framework of this study. In summary, a total of 160 complete responses were required, considering eight predictors, an effect size of 0.15, and a significance level of $\alpha = 0.05$ (see Figure 4.1).

Table 4.1 : Sample Size Power

Power	Minimum Sample Size
0.75	99
0.8	108
0.85	120
0.9	135
0.95	160

(Source: Extracted from G* power 3.1 Software)

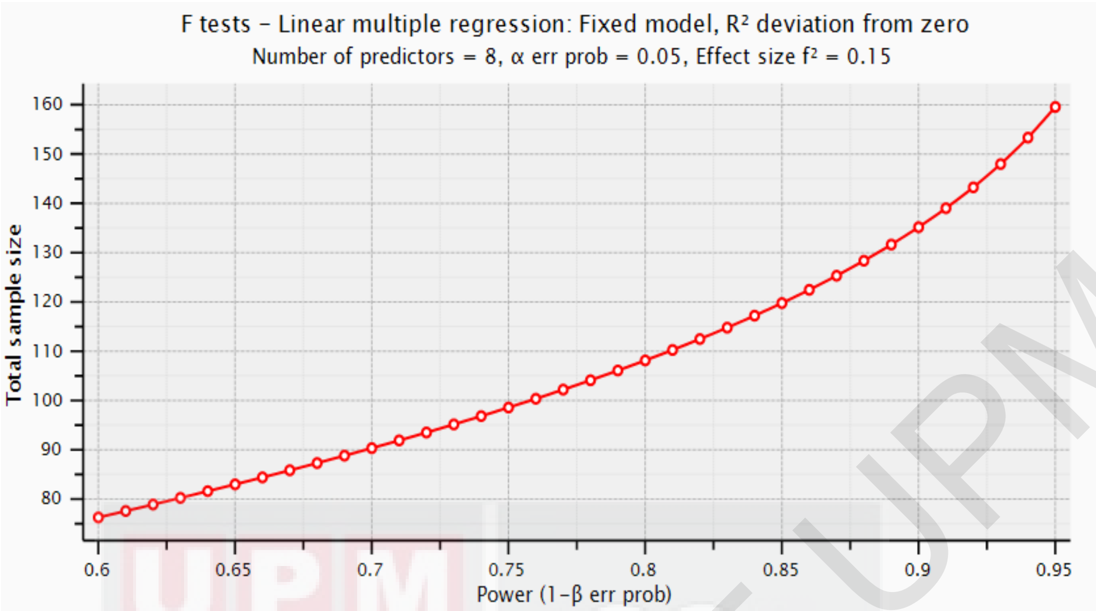

Figure 4.1 : Statistical Power in a Complex Model
(Source: Extracted from G power*3.1 Software)

In summary, the sample size for this study was determined by considering various perspectives. First, Hair et al. (2018) asserted that any sample size exceeding 200 is deemed sufficient for statistical analysis. Second, following the ten-fold rule outlined by Hair et al. (2016), the framework for this study required 80 complete responses. Third, the results of the power analysis revealed that a minimum sample size of 160 samples is recommended for the current research model. Lastly, Sekaran and Bougie (2013) suggested that a sample size of around 500 is large enough to obtain robust results. Generally, to minimise errors in completing the questionnaires, such as missing values, illegibility, inconsistent responses, and non-responses, a conservative sample size of 500 is used.

4.6 Sampling Techniques

According to Kothari (2019), a good sample is truly representative of the study population. Proper sampling can improve the accuracy and generalisability of the results. In general, there are two types of sampling techniques: probability sampling and non-probability sampling (Saunders et al., 2019).

In probability sampling, the selection of the sample is random, and each case in the population has an equal chance of being selected (Levy & Lemeshow, 2013). This method is often accomplished using an exact sampling frame that provides a list of names for each case. Thus, a random sample is most likely to represent the total population (Babbie, 2015). On the other hand, sample selection in non-probability sampling is based on the judgment of the individual researcher. The probability of each case being selected is unknown. In fact, non-probability sampling techniques are often employed in human-related research because it is unlikely that the researcher would get a complete list of the populations that allow for random selection (Saunders et al., 2019).

However, non-probability sampling is often challenged as producing results that may not fully reflect overall characteristics. Cooper and Schindler (2011) refute this argument by arguing that non-probability sampling techniques can produce valid and useful results if used wisely by researchers. Most theory-testing studies emphasise theory generalisation over sampling generalisation (Hulland et al., 2018; Memon et al., 2017). In fact, non-probability sampling techniques are more suitable for most marketing research because it is difficult to obtain a complete list of all consumers in a population group, i.e., a sampling frame is not available (Rowley, 2014; Saunders et al., 2019). In general, non-probability sampling includes purposeful (judgmental) sampling, convenience sampling, snowball sampling, and quota sampling (Saunders et al., 2019). Table 4.2 lists the advantages and disadvantages of various non-probability sampling techniques.

Table 4.2 : Comparison of Non-Probability Sampling Techniques

Name	Cost/ Degree of Use	Advantages	Disadvantages
Convenience	Very low cost; extensively used	No need for a list of the population	Sample may not be representative; Random sampling error cannot be estimated; Predicting data outside the sample is relatively risky
Purposive	Moderate cost, average use	Selected sample is based on research objectives; Minimises risk of sampling frame error	Expert bias can lead to an unrepresentative sample; Projecting data beyond the sample is risky
Quota	Moderate cost, average use	Sample selection based on pre-specified characteristics; Adequately inclusion of subgroups in the population	Introduces bias in the researcher's classification of subjects; Non-random selection within categories means errors from the population cannot be estimated; Predicting data outside the sample is risky
Snowball	Low cost; used in special situations	Helpful in identifying members of rare populations	High bias as sample units is not independent; Predicting data outside the sample is risky

In this study, the quota sampling technique was used after considering its advantages and disadvantages. This technique enables the sub-groups (platforms) in the population to be adequately included while ensuring that the sample offers meaningful information for the study (Saunders et al., 2019). Thus, the appropriate numbers of respondents were calculated in each platform category. The number of active users on Douyin, Kuaishou, and Xiaohongshu is 680 million, 390 million, and 200 million, respectively. Correspondingly, the sample sizes for these three platforms are 270, 155, and 75, respectively. In addition, the criteria in selecting respondents for each platform were that each respondent must (1) come from the Chinese Mainland, (2) be a millennial born between 1981 and 1996, and (3) have had a purchase experience with live streaming commerce on a content-sharing platform within the last three months.

These respondent criteria align with the study's objective of investigating users' purchase intentions, ensuring that the sample can provide relevant information for the study.

4.7 Data Collection Method

Research data can be categorised into primary and secondary data. Primary data are the original data collected by the researcher for a specific purpose; secondary data are the existing data in the database collected for other purposes (Bishop & Kuula-Lummi, 2017). Considering the research objectives of this study, primary data was chosen as the main data source.

In this study, the primary data was collected using a survey method (Saunders et al., 2019). The survey method is widely recognised as one of the most popular and extensively used approaches in marketing research (Li et al., 2021; Liu et al., 2012; Malhotra et al., 2017), as it enables a large number of individuals to be asked standard questions (Saunders et al., 2019). The questionnaire is a widely used survey approach in business and management research due to its efficiency in gathering responses from a diverse sample using a standardised set of questions (Saunders et al., 2019). Moreover, online surveys conducted through desktop and mobile devices offer the advantage of minimising contamination or distortion of respondents' answers while enabling convenient storage and analysis of electronic data (Saunders et al., 2019). Hence, online questionnaires were selected as the method of data collection for this study.

The questionnaire was created and delivered via the internet platform Wenjuanxing, which is a highly reputable Chinese version of Qualtrics. This approach enabled the researcher to dispense with data entry (Saunders et al., 2019). In addition, the quality of the data was improved through the logic and validity checks of the platform (Malhotra et al., 2017). A pre-screening question was employed in this study to ensure the validity of the questionnaire responses. Only those who answered affirmatively to the following questions were permitted to proceed: (1) "Are you from mainland China?"; (2)"Are you born between 1981 and 1996?"; and (3) "In the last three months, have you had live streaming shopping experience on any of the three platforms (Douyin, Kuaishou, Xiaohongshu)?". Online distribution was conducted by posting the questionnaire links through social media such as WeChat shopping groups, QQ shopping groups, Xiaohongshu shopping groups, and microblogs. The selection of these specific channels for questionnaire distribution increased the likelihood that the respondents were already live streaming commerce users, thus further understanding their perceptions.

4.8 Research Instrument

Research instruments are measurement tools that researchers use to measure proposed constructs (Saunders et al., 2019). Researchers access instruments in three ways: (1) developing their own items, (2) adapting items from past academic research by changing them to fit the current research context, or (3) completely adopting items from past academic research (Creswell, 2014). When no suitable instrument is available in the literature, researchers can create a new one. However, this process is more arduous and extensive, requiring a series of validity and reliability tests before application in an empirical study. On the other hand, when adopting or adapting established instruments, the chosen instruments should meet certain criteria, which can increase content validity (Creswell, 2014). For example, the instruments should ideally be frequently mentioned by others and support the research question or hypothesis.

In this study, all instruments for the constructs outlined in the research framework were carefully selected from the existing literature and adapted to the context of live streaming commerce. Adaptation of the questionnaire is beneficial if the study focuses on theory testing (Hulland et al., 2018). A list of the measurement scales can be seen in Section 4.8.3 (see Table 4.4).

4.8.1 Development of the Questionnaire

In this study, the questionnaire was divided into four sections. Section A recorded respondents' live streaming commerce usage, sections B and C captured variables (constructs), and section D recorded respondents' demographic information. All items were designed as closed-ended statements to provide respondents with multiple choices, thus reducing their burden in answering the questionnaire (Ringle et al., 2010). In addition, this design was thought to elicit higher response rates and simplify the data analysis process (Creswell, 2014).

Considering that most live streaming commerce platforms appear in Chinese when users select mainland China as their geographic location, the questionnaire in this study was translated from English to Chinese using Brislin's (1980) back-translation techniques. This approach ensured that the questions were effectively understood by the respondents and minimised any potential language barriers.

4.8.2 Demographic Questions

This study used nominal and ordinal scales to understand the usage patterns and demographics of the respondents in live streaming commerce. Nominal scale is a categorical scale used to count the frequency of occurrences within each category of a variable (Saunders et al., 2019). The values in this scale are often used for identification purposes. The ordinal scale is a more precise form of categorical scale. It allows the researcher to discern the relative location of each example in the dataset (Saunders et al., 2019).

Specifically, in Section A, two questions (i.e., "Which of the following is your preferred live e-commerce application?" and "Which of the following are the products you most often purchase through live streaming commerce?") were measured using the nominal scale. The other two questions were measured using the ordinal scale (e.g., “How long have you been using live streaming commerce?” and "How often do you make purchases on Live Commerce?") (see Table 4.3). In Section D, the nominal scale was used to measure gender and occupation, while the ordinal scale was used to measure age, highest level of education, and monthly income (see Table 4.3).

Table 4.3 : List of Demographic Questions

Section A: Live Streaming Commerce Usage	Scale of Measurement
1) Which of the following is your PREFERRED live streaming commerce platform? (Please tick "" one box only)? □ Douyin □ Kuaishou □ Xiaohongshu	Nominal Scale
2) How long have you been using live streaming commerce? □ 3-6 months □ 7-12 months □ 13-18 months □ 19-24 months □ 25-30 months □ 31 months and above	Ordinal Scale
3) How often do you make purchases on Live Commerce? □ Daily □ Weekly □ Monthly □ Once every 2-3 months □ Once every 4-6 months □ Once a year or less	Ordinal Scale

Table 4.3 : Continued

4) Which of the following is the product that you most frequently purchase via live streaming commerce? (You may tick "?" more than one box)? □ Apparel □ Daily Household □ Cosmetics □ Food & Health □ Sports & Travel □ Books & Audio □ Electronic □ Jewellery □ Maternal and Child	Nominal Scale
Section D: Respondent Profile	**Scale of Measurement**
1) Gender □ Male □ Female	Nominal Scale
2) Age □ 27-30 years old □ 31-35 years old □ 36-42 years old	Ordinal Scale
3) Highest Level of Education □ Second school or below □ Junior college □ Undergraduate Degree □ Graduate Degree □ Postgraduate Degree	Ordinal Scale
4) Occupation □ Employee - Government sector □ Employee - Private sector □ Self-employed □ Student □ Others	Nominal Scale
5) Monthly Income □ Less than RMB 3,000 □ RMB 3,001- RMB 5,000 □ RMB 5,001-RM 7,000 □ RMB 7,001-RMB 9,000 □ RMB 9001-RMB11,000 □ RMB 11001-RMB13,000 □ RMB 13001-RMB15,000 □ More than RMB 15,000	Ordinal Scale

4.8.3 Measurement Items for Constructs

This study used the interval scale to measure all variables with 39 questions spanning eight constructs: expertise, attractiveness, interaction orientation, media richness, personalisation, swift guanxi, purchase intention, and PEEIM. Utilising the interval scale allowed researcher to interpret differences with greater precision. To ensure accuracy, all measurement items were selected from validated scales and were adjusted to align with the specific context of this study.

Expertise and attractiveness were assessed using Guo et al.'s (2022) scale, comprising four items and three items, respectively. A seven-item scale for interaction orientation was adapted from Williams and Spir (1985), a four-item scale for media richness was adapted from Ma (2021), and a three-item scale for personalisation was adapted from Liu et al. (2021). Swift guanxi was evaluated using Ou et al.'s (2014) 12-item three-dimensional scale, encompassing mutual understanding, reciprocal favours, and relationship harmony. For assessing purchase intention, four items were adapted from Pavlou and Gefen's (2004) scale. PEEIM was measured with three items, utilising Fang et al.'s (2014) scale. The detailed list of measurement items for each construct is given in Table 4.4.

To capture respondents' attitudes towards these constructs, a Likert scale was used, which is a widely used technique for measuring items and evaluating different degrees of agreement (Hair et al., 2016). The exogenous and endogenous factors were measured using a 5-point Likert scale, ranging from "1-strongly disagree" to "5-strongly agree". To ensure participants were attentive of the questionnaire structure, a specific instruction was included (e.g., "This section focuses on your perception of our PREFERRED live streaming commerce platform (see your response in Q1, Section A) and the specific streamer with whom you have had purchasing experiences on that platform").

Table 4.4 : List of measurement items for Each Variable

Latent Variable	Coding	Measurement Item	Reliability	Source
Expertise	EX1	The live streamers are expert in products.	α=0.840	(Guo et al., 2022)
	EX2	The live streamers have experience in products.		
	EX3	The live streamers are very knowledgeable about products.		
	EX4	The live streamers provide substantial information regarding products.		
Attractiveness	AT1	The live streamers are quite handsome/pretty.	α=0.900	(Guo et al., 2022)
	AT2	The live streamers are attractive physically.		
	AT3	I feel the live streamer is very good looking.		
Interaction orientation	IO1	The live streamers genuinely enjoy helping audiences.	α=0.85	(Williams & Spiro, 1985)
	IO2	The live streamers are easy to talk with.		
	IO3	The live streamers like to help audiences.		
	IO4	The live streamers are a cooperative person.		
	IO5	The live streamers try to establish a personal relationship.		
	IO6	The live streamers seem interested in me not only as a customer, but also as a person.		
	IO7	The live streamers are friendly.		
Media Richness	MR1	The live-stream channel allows me to give and receive timely feedback.	CR=0.978; AVE=0.919	(Ma, 2021a)
	MR2	The live-stream channel helps me communicate quickly		
	MR3	The live-stream channel allows users to communicate with different types of messages, such as audio, video, text, and stickers.		
	MR4	The live-stream channel helps me better understand others and satisfy each other's needs.		
Personalisation	PS1	The live-stream channel understands my personalised needs.	CR=0.824; AVE=0.524	(Liu et al., 2021)
	PS2	The live-stream channel offers me targeted recommendations based on my preferences.		
	PS3	The live-stream channel meets my personalised needs basically.		

Table 4.4 : Continued

Swift guanxi (Mutual understanding)	MU1	The live streamers and I understand each other's needs.	CR=0.939; AVE=0.755	(Ou, Pavlou, & Davison, 2014)
	MU2	The live streamers and I understand each other's point of view.		
	MU3	The live streamers and I can make ourselves heard.		
	MU4	The live streamers and I can follow the flow of conversation		
	MU5	The live streamers and I show interest in each other's opinions		
Swift guanxi (Reciprocal favours)	RF1	If I buy from the live streamer, he/she will provide a discount for me.	CR=0.913; AVE=0.724	(Ou, Pavlou, & Davison, 2014)
	RF2	The live streamers and I offer positive ratings or comments to each other.		
	RF3	The live streamers and I help each other.		
	RF4	The live streamers and I proved to be friends by doing favours for each other.		
Swift guanxi (Relationship harmony)	RH1	The live streamers and I maintain harmony.	CR=0.903; AVE=0.756	(Ou, Pavlou, & Davison, 2014)
	RH2	The live streamers and I avoid conflict.		
	RH3	The live streamers and I respect each other.		
Purchase Intention	PI1	Given the chance, I predict that I would consider purchasing products from streamers on this platform in the future.	CR=0.950; AVE=0.860	(Pavlou & Gefen, 2004)
	PI2	It is likely that I will actually purchase products from streamers on this platform.		
	PI3	Given the opportunity, I intend to purchase products from streamers on this platform.		
PEEIM	PEE1	When buying on this platform, I am confident that there are mechanisms in place to protect me against any potential risks (e.g. leaking of personal information, credit card fraud, goods not received, etc.) of online shopping if something goes wrong with my online purchase.	CR=0.890; AVE=0.739	(Fang et al., 2014)
	PEE2	I believe that there are other parties (e.g. my credit card company) who have an obligation to protect me against any potential risks (leaking of personal information, credit card fraud, goods not received, etc.) of online shopping if something goes wrong with my online purchase.		
	PEE3	I am sure that I cannot be taken advantage of (e.g. leaking of personal information, credit card fraud, goods not received, etc.) as a result of conducting purchases on this platform.		

4.9 Pre-Test and Pilot Test

Prior to using the questionnaire for actual data collection, it is recommended for the questionnaire to be pre- and pilot tested (Saunders et al., 2019). It is often difficult for researchers to detect and suppress all potential problems during data collection (Hulland et al., 2018). Therefore, initial steps (i.e., pre-test and pilot test) are necessary before distributing the questionnaire to all respondents, and they identify errors and weaknesses in the instrument from both experts' and respondents' perspectives (Creswell, 2014).

This study developed a bilingual questionnaire in Chinese and English, as the data were collected in China. To ensure accurate translation, a professor and a PhD student with expertise in information systems and marketing, both fluent in Chinese and English, were invited to translate the questionnaire items carefully. Subsequently, a pre-test and pilot study were conducted to establish content validity. According to Willis (2004), an appropriate pre-test sample size ranges from 5 to 15 respondents. Some research even suggests that testing a questionnaire with just one individual can be more beneficial than administering it without pre-testing. Based on above, a panel of six participants was involved for the pre-test in this study: three experts from the marketing field (including marketing managers and marketing professors specialising in digital marketing or consumer behaviour) and three experienced millennial live streaming shoppers with at least an undergraduate education. Their feedback were used to evaluate the questionnaire's quality, focusing on aspects such as wording, readability, relevance, and applicability to the research context (Bougie & Sekaran, 2013). Based on the advice of the panel, the questionnaire was revised to ensure that the items were clear and precise. A list of comments from the pre-test is attached in

Table 4.5.

After pre-testing, the questionnaire underwent a pilot test. A pilot study serves as a trial run for the overall study, enhancing its probability of success. Specifically, it serves three major purposes: (1) to conduct an initial evaluation of the constructs' internal consistency; (2) to refine the questions, format, and instructions; and (3) to provide an opportunity to assess how long the study will take and to identify potential participant fatigue issues (Saunders et al., 2019). The sample size for a pilot test is determined by various criteria. Cooper and Schindler (2011) suggest using a sample size between 25 and 100 individuals. Isaac and Michael (1995) assert that 10 to 30 participants are adequate for a pilot test. Alternatively, some researchers suggest that the sample size should be 10% of the expected sample in the main study (Turel et al., 2008). Traditionally, a sample size of 30 respondents is typically recommended. This number is derived from the Central Limit theorem, which makes a distribution assumption regarding a sample size greater than 30 to ensure that the average of any sample drawn from the target population will be roughly equal to the average population (Memon et al., 2017). In this study, a pilot test was conducted by distributing questionnaires to 30 Chinese millennials who had prior experience in live streaming commerce. Reliability testing of the pilot test data indicated that the Cronbach's alpha values for all constructs exceeded 0.70 (Tavakol & Dennick, 2011), as shown in Table 4.6, indicating internal consistency of the measurement items. In conclusion, the results from both the pretest and pilot test in this study contributed to enhancing the clarity of the statements and the structure of the questionnaire, guaranteeing improved readability.

Table 4.5 : Comments from the pre-test and Pilot Test

Comments		Revision (Yes/No)
Cover Page:		
1	Improve structure and logical order.	Yes
2	Clarify the purpose and focus of the investigation.	Yes
3	Revise the spelling and the tense errors.	Yes
Section A: Live Streaming Commerce Usage		
1	Allow the respondent to select more than one answer for Q4 (i.e. Which of the following is the product that you most frequently purchase via live streaming shopping?)	Yes
2	Correct the spelling mistakes.	Yes
Section B: Perception towards the Live streaming commerce		
1	Add a reminder for each variable to remind the respondent to respond to the statement by anchoring to their preferred live streaming commerce platform.	Yes
2	Add a header for all the scales.	Yes
3	Make the wording consistent as either British or American English.	Yes
4	Make sure all the items have been adapted to the context of the study.	Yes
Section C: Individual Differences		
1	Reduced use of jargon.	Yes
2	Correct the spelling mistakes.	Yes
Section D: Demographic Profile		
1	Revise the selection for age group, make sure it covers all the target population.	Yes
2	Some occupations are redundant and need to be revised.	Yes

Table 4.6 : Pilot Test Reliability Results

No.	Construct	Cronbach's alpha
1	Attractiveness	0.711
2	Expertise	0.861
3	Interaction Orientation	0.919
4	Media Richness	0.899
5	Mutual Understanding	0.905
6	PEEIM	0.761
7	Personalisation	0.847
8	Purchase Intention	0.809
9	Reciprocal Favours	0.752
10	Relationship Harmony	0.874

4.10 Data Analysis Method

After data collection was completed, data analysis followed. Data analysis is performed to allow researchers to clearly understand the relationship between variables. Two statistical software packages were used for data analysis in this study. Descriptive analysis was conducted using the Statistical Package for Social Sciences software (SPSS v.26) to understand the frequencies and percentages of demographic attributes of the sample respondents. Partial Least Square Structural Equation Modelling (PLS-SEM) with the Smart PLS 4.0.9 software was used to assess the measurement model and structural model. The measurement model, also referred to as the outer model, was used to assess the relationship between the indicator and their corresponding constructs. The structural model, also known as the inner model, specifies the relationships between constructs (Hair et al., 2014).

4.10.1 Data Preparation

Data preparation consists of three steps (Zikmund et al., 2013). Initially, each item of the questionnaire was given a distinct code. Following this, the data were systematically entered into the software. Next, data cleaning was used to ensure the data are clean, reliable, and valid to be analysed. Stephen (2015) proposed using data cleaning in research to (1) eliminate human errors when entering data; (2) avoid suspected outliers that can be greater or less than most observations; and (3) identify missing values; Therefore, frequency and descriptive tests were used to detect input errors, while expectation maximisation techniques were used to treat cases with missing values in this study.

Subsequently, scholars suggested specific statistical remedies to be used in the data preparation phase to address common method variance (CMV). Podsakoff (2003) suggests that CMV should be given special consideration in empirical studies, particularly when adopting self-reported questionnaires to obtain data. CMV can lead to internal consistency and bias when evaluating the relationship between variables, leading to Type I and Type II errors.

Specifically, Harman's Single Factor was recommended for assessing CMV using the SPSS software to analyse the principal component factors. Babin et al. (2016) asserted that CMV is deemed to not exist if a factor does not account for the majority of variance beyond 40%. However, Podsakoff et al. (2003) suggested that CMV might be considered absent if a factor does not explain more than 50% of the variance. Additionally, PLS-SEM was also employed to conduct a full collinearity test to identify potential CMV issues. This technique provides an integrated evaluation of vertical and lateral covariance, and CMV is considered absent if all Variance Inflation Factor (VIF) values fall below a threshold score of 3.33 (Kock & Lynn, 2012).

Normality was assessed after data preparation. Normality testing is recognised as one of the most important analytical steps in quantitative research. Skewness and kurtosis are the most important indicators for assessing the distribution of data (i.e., normal or non-normal distribution) (Mardia, 1970). Specifically, skewness refers to the degree of symmetry, while kurtosis refers to the peaks of a data set. This study used Mardia's coefficient to assess multivariate skewness and kurtosis (Mardia, 1970). This statistical formula compares the joint distribution of many variables to a multivariate normal distribution (Cain et al., 2017). In other words, when using this measure, researchers can simultaneously test the normality of the overall model. When skewness and kurtosis approach zero, the response obeys a normal distribution. Nevertheless, such an occurrence is improbable. Byrne's (2013) and Kline's (2015) guidelines state that when evaluating the multivariate coefficients for Mardia's, a kurtosis coefficient values greater than 20 indicate that the multivariate data are non-normally distributed. After these preliminary analyses, the data were evaluated using PLS-SEM.

4.10.2 Analysing the Data

Structural equation model (SEM) is a second-generation statistical analysis technique utilised to examine the complex interrelations among multiple variables within a model (Chin, 1998; Hair, Matthews, et al., 2017). SEM integrates two robust statistical methods (factor analysis and structural path analysis), which allows the simultaneous evaluation of measurement models and structural models (Hair, Matthews, et al., 2017; Lee et al., 2011). In addition, SEM explains more variance in the dependent variable compared to multiple regression, as it explains both direct and indirect effects (Lee et al., 2011). Therefore, SEM is widely used across a wide range of disciplines, including marketing research (Henseler et al., 2012). There are two common types of SEM: variance-based (CB-SEM) and partial least squares (PLS-SEM). These two approaches are complementary (Hair, Matthews, et al., 2017), and the use of the right approach depends on the objectives of the study (refer to Table 4.7).

First, CB-SEM is a confirmative method for testing and confirming theories, requiring a comprehensive theoretical model and well-defined indicators prior to data analysis (Hair et al., 2017). In contrast, PLS-SEM is a prediction-oriented method applicable to both exploratory and confirmatory research (Sarstedt et al., 2014). Therefore, PLS-SEM is more suitable for theory formulation and testing.

Second, CB-SEM has stricter data requirements. CB-SEM must conform to a variety of assumptions, including the multivariate normality of the data and the minimum sample size (Hair et al., 2017). When the assumptions are not satisfied or violated, CB-SEM results can be very imprecise. In contrast, PLS-SEM can analyse non-normal distributions, and the system can transform any non-normally distributed data into data satisfying the central limit theorem (Hair, Matthews, et al., 2017). Thus, PLS-SEM can yield more robust structural model estimations (Hair et al., 2011; Reinartz et al., 2009).

Third, PLS-SEM can manage complex models containing formative measurements, reflective measurements, and higher-order constructs, whereas CB-SEM is limited to studying reflective measurements (Chin, 1998). The interpretation of the covariance of all indicators is impossible when the formative measurements are applied in CB-SEM (Chin, 1998). Therefore, dealing with both formative and reflective measurements in CB-SEM is more complicated (Chin, 1998). On the contrary, PLS-SEM provides a hierarchical component method and is appropriate for modelling second-order structures with formative measurement (Chin, 1998).

Table 4.7 : The Rules of Thumb for CB-SEM and PLS-SEM

Criteria to Evaluate	CB-SEM	PLS-SEM
Research Goals	Theory testing, theory confirmation	Predicting target constructs Both exploratory and confirmatory
Measurement Model	Error terms need extra explanation, including co-variation	Inclusion of formative constructs
Structural Model	Structural model is non-recursive	Structural model is complicated
Data Characteristics and Algorithm	Large sample size; Normally distributed;	Both small and large sample size; Normal and nonnormal distributed;
Model Evaluation	Requires global goodness of fit criterion; Test for measurement model invariance is required	Latent variable scores in subsequent analyses

(Source: Hair et al., 2011)

In general, when CB-SEM assumptions cannot be satisfied, complex constructs are included, or the purpose of the study is to predict rather than confirm structural relationships, PLS-SEM is the recommended technique. Thus, it is appropriate to use PLS-SEM in this study, which places more emphasis on prediction than model comparison. Furthermore, this study aims to examine a relatively new phenomenon that explores potential factors influencing users' purchase intention in live streaming commerce. Meanwhile, swift guanxi is considered a reflective-formative higher-order construct, while other constructs, such as expertise, attractiveness, and purchase intention, are considered reflective. Therefore, this study used PLS-SEM to analyse its data.

4.10.3 Measurement Specifications in PLS-SEM

The evaluation procedure for PLS-SEM often comprises two sets of models: the inner model (structural model) and the outer model (measurement model) (refer to Figure 4.2). The measurement model is divided into two types: reflective and formative models (Hair et al., 2016).

In a reflective measurement model, the construct is viewed as a reflection of interchangeable indicators. The removal of any indicator does not change the overall meaning of the construct. Conversely, a formative measurement model implies that each indicator holds a specific meaning in explaining the construct, rendering the indicators non-interchangeable. Omitting any indicator from a formative model may compromise the validity of the variables (Hair et al., 2016; Sarstedt et al., 2014). It is worth noting that reflective and formative measurement models are characterised by arrows pointing in opposite directions. In a reflective model, the arrow points from the construct to the indicators, whereas in a formative model, the arrow points from the indicators to the construct (refer to Figure 4.2).

Moreover, a special construct type in measurement models is known as a higher-order construct (HOC) or hierarchical component models (HCMs). HOCs comprise a more abstract higher-order component and several concrete sub-dimensions termed as lower-order components (LOCs) (Cheah et al., 2018; Hair et al., 2016). Utilising HOCs offers benefits such as (1) reducing redundancy and complexity for model simplicity; (2) addressing collinearity issues when sub-dimensional components share similar meanings by grouping them under the same higher-order component; and (3) presenting a construct with multiple sub-dimensions, thereby refining its definition accuracy (Cheah et al., 2018). However, the use of HOCs should rest on robust theoretical foundations and appropriate methodological approaches (e.g., repeated indicators, two-stage, or hybrid approach) (Sarstedt et al., 2019). Researchers also need to differentiate between different HOC types (e.g., reflective-reflective,

reflective-formative, formative-reflective, and formative-formative) and handle them accordingly (Cheah et al., 2018).

In general, the underlying rationale for these assessments is to ensure the accuracy of measurements representing constructs before delving into the analysis of structural relationships (Hair et al., 2016). The detailed guidelines for evaluating the models are discussed in the subsequent sections.

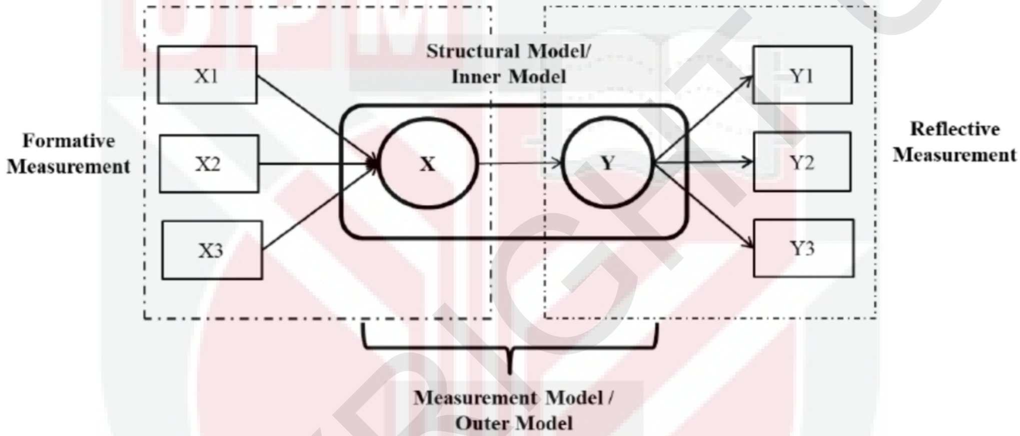

Figure 4.2 : Models in PLS-SEM

4.10.4 Evaluation of Measurement Model

In the measurement model, the assessment centres on ensuring the reliability and validity of the constructs (Hair et al., 2014). Table 4.8 presents a summary of guidelines for evaluating the reflective and formative measurement models.

Reflective Measurement Model

There are three tests that are commonly used to check reflective measurement models: internal consistency, convergent validity, and discriminant validity.

i. Internal Consistency

Cronbach's alpha (α) is commonly used to assess the internal consistency of a construct, meaning it assesses the average consistency across all items (Cronbach, 1971). Hair et al. (2019) suggested a value of alpha (α) greater than 0.70 to be acceptable. As the value rises, the reliability of the model improves. Yet, if the value surpasses 0.95, it suggests redundancy among the items (Hair, Risher, et al., 2019). Despite its widespread use, some researchers claim that Cronbach's alpha underestimates the structure's internal consistency (Hair, Risher, et al., 2019). This measure is sensitive to the number of items and is influenced by Tau-equivalent. As an alternative, Gefen et al. (2000) proposed utilising composite reliability (CR) to assess internal consistency as it considers the different weights of the indicators (Dijkstra & Henseler, 2015; Hair et al., 2014). Generally, it is a common practice for researchers to report both α and CR values where the threshold of 0.70 and above is considered satisfactory.

ii. Convergent Validity

In the reflective measurement model, the evaluation of convergent validity depends on the outer loading values and the average variance extracted (AVE). A higher outer loading value indicates that the indicator is an important component of a specific construct. Outer loadings of 0.708 or above are deemed acceptable, as they signify that a construct accounts for at least fifty percent of the indicator's variance (Hair, Sarstedt, et al., 2017). Conversely, when external loadings fall below 0.4, it is recommended to remove the corresponding item (Hulland, 1999; Ramayah et al., 2016). Moreover, convergent validity can be evaluated using the AVE of the construct. An AVE greater than 0.5 is considered appropriate, suggesting that the reflective construct elucidates more than 50% of its indicators (Hair, Sarstedt, et al., 2019).

iii. Discriminant Validity

Discriminant validity describes the extent to which one construct in a structural model differs from the other constructs (Hair, Sarstedt, et al., 2017). Two primary methods are commonly used to evaluate discriminant validity. First, the Fornell-Larcker criterion for discriminant validity was applied. However, it has been criticised by some researchers for its limited capacity to discriminate between the metric loadings, for example, when all indicators are loaded within the range of 0.65 to 0.85. As an alternative, the Heterotrait-Monotrait (HTMT) ratio of correlations (Henseler et al., 2015) was recommended to measure the correlations within the constructs against the correlations between the constructs. This approach measures the ratio of the mean value of different inter-conformational metric correlations to the mean value of the same inter-conformational metric correlations (Hair, Sarstedt, et al., 2017; Voorhees et al., 2016). HTMT values below 0.90 or 0.85 are considered acceptable (Voorhees et al., 2016).

Formative Measurement Models

Evaluating formative measurement models involves assessing collinearity, convergent validity, the indicators' outer weights, and significance (Hair et al., 2019; Sarstedt, et al., 2017).

i. Collinearity Issues

Collinearity issues arise when two formative predictors have a strong correlation. Severe collinearity issues can generate incorrect path coefficients and directions, leading to erroneous interpretations (Hair et al., 2017, 2019). The VIF is commonly used to assess collinearity issues in formative indicators. When the VIF exceeds 5, the collinearity problem is generally considered severe, whereas a value below 3 indicates satisfactory results (Hair et al., 2017, 2019).

ii. Convergent Validity

Convergent validity refers to the extent to which different indicators are interconnected within the same formative construct (Hair et al., 2017, 2019). This can be evaluated through redundancy analysis using a global-single item (Cheah et al., 2018; Chin, 1998). In fact, redundancy analysis is done by modelling the formative construct as the exogenous variable linked to the global single item (i.e. endogenous variable) (Cheah et al., 2018). A path coefficient larger than 0.70 suggests satisfactory convergence validity (Cheah et al., 2018; Hair et al., 2017).

iii. Indicator Outer Weight and Significance

The indicator's weight and significance indicate how much each formative indicator contributes to the formation of the construct. Bootstrapping techniques are frequently employed to evaluate the importance of the outer weights of the indicators. Hair et al. (2017) claimed that indicator weights are normalised to values ranging from -1 to 1. Close to 0 weights indicate a weak connection between the indicator and the construct. In contrast, weights close to +1 (or -1) suggest a significant positive (or negative) association. On the other hand, insignificant formative indicators should not be immediately deleted (Hair, Sarstedt, et al., 2017). Instead, theoretical concerns should always govern the choice to eliminate or keep non-significant formative indicators (Hair et al., 2011; Ramayah et al., 2016). If theoretical conceptualisation substantially supports the formative indicator, researchers should keep an insignificant formative indicator (Hair, Sarstedt, et al., 2019) to avoid losing content validity (Diamantopoulos & Winklhofer, 2001).

Table 4.8 : Summary of Assessment of Reflective and Formative Measurement Model

Measure Model	Assessment	Criterion	Rule of Thumb
Reflective	Internal Consistency	Cronbach's Alpha	$\alpha>0.70$
		Composite Reliability (CR)	CR>0.70 (Hair, Risher, et al., 2019)
	Convergent Validity	Outer Loadings	Outer loadings > 0.708 (Hair, Matthews, et al., 2017); Or if the construct's AVE > 0.50, the outer loadings > 0.40 is regarded acceptable
		Average Variance Extracted (AVE)	AVE >0.50 (Bagozzi & Yi, 1988; Fornell & Larcker, 1981)
	Discriminant Validity	Fornell-Larcker Criterion	The square root of AVE > The correlations between the construct and other constructs (Fornell & Larcker, 1981).
		HTMT Criterion	HTMT < 0.85 (Kline, 2015)
Formative	Collinearity Issues	Variance Inflation Factor (VIF)	VIF < 5 (Hair et al., 2011); VIF < 3 (Hair et al., 2019)
	Convergent Validity	Redundancy Analysis	Redundancy analysis with path coefficient > 0.70 (Cheah et al., 2018; Hair et al., 2017)
	Significance and Relevance of Outer Weight		Achieved a significant result via bootstrapping procedure ($p < 0.05$)

4.10.5 Structural Model

The evaluation of the structural model consists of five steps: collinearity problem, path coefficients, the coefficient of determination (R^2), effect size R2(f^2), and predictive correlation (Q^2 and PLSpredict). Following this was an evaluation of the moderating and mediating effects.

i. Collinearity Issues

It is critical to ensure that no collinearity issues occur within the structural model. Even when discriminant validity is satisfied, collinearity issues can sometimes mislead the results because it can alter the strength of the path, particularly when two constructs, assumed to be causally linked, are actually measuring the same construct (Kock & Lynn, 2012). Similar to the formative measurement model, collinearity problems in the structural model can be evaluated using VIFs. Likewise, the VIF value should be less than 5.0 (Hair et al., 2011), or, for a more rigorous criterion, the VIF value ought to be below 3.3 (Diamantopoulos & Siguaw, 2006).

ii. Path Coefficients

The level of the path coefficient indicates the significance of the proposed relationship. The path coefficient values are normalised between -1 and 1. In particular, values close to +1 suggest a high positive correlation between constructs, while values near -1 indicate a strong negative correlation, and values near 0 indicate a weaker association. Given the nonparametric assumptions of PLS-SEM, bootstrap approaches were utilised to determine standard errors and test for statistical significance (Hair, Sarstedt, et al., 2019). Typically, three criteria are used to determine whether path coefficients are statistically significant: (1) p-values less than 0.05, (2) t-values greater than 1.645

for one-tailed tests, t-values greater than 1.96 for two-tailed tests, or (3) The zero value is not included between the upper and lower limits of the confidence interval.

iii. Coefficient of Determination (R^2)

Coefficient of Determination (R^2) is presented as the in-sample predictive power (Rigdon, 2012). The R^2 value represents the proportion of variance in the endogenous variable explained by the exogenous variables (Hair et al., 2019). The R^2 value ranges from 0 to 1, with higher values implying greater predictive accuracy. Researchers typically adhere to Cohen's (1988) guideline, wherein values of 0.02, 0.13, and 0.26 are indicative of low, moderate, and high degrees of predictive accuracy, respectively.

iv. Effect Size (f^2)

Subsequently, Cohen's f^2 is used to determine the effect size of each exogenous construct. The f^2 is calculated by computing the change in R^2 when a construct is removed from the model (Hair et al., 2017). Empirically, 0.02, 0.15, and 0.35 are considered small, medium, and large effect sizes, respectively (Cohen, 1988; Hair et al., 2019).

v. Predictive Relevance (Q2 and PLSpredict)

Finally, the predictive relevance of the model can be tested using Stone and Geisser's Q2 (Stone, 1974) through the blindfolding technique in the PLS-SEM software. For a particular endogenous structure, a Q^2 value above 0 confirms its predictive accuracy. Subsequently, out-of-sample prediction is conducted. Specifically, predictive ability is measured based on training samples (Shmueli et al., 2019). In PLS-SEM, PLSpredict is utilised to create a case level prediction at a construct level (Shmueli et al., 2016). Initially, the Q^2 predicted is used to determine whether the predictions surpass the naïve benchmark, with a positive Q^2 predicted value indicating a small prediction error (Shmueli et al., 2019). Then, the researchers compare the predicted statistics (RMSE and MAE) with the naïve benchmark through results generated from a linear regression model. Lastly, the results are interpreted using the guidelines suggested by Shmueli et al. (2019):

1) Lacks predictive power: PLS < LM for none of the indicators.
2) Low predictive power: PLS < LM for a minority of the indicators.
3) Medium predictive power: PLS < LM for a majority of the indicators.
4) Large predictive power: PLS < LM for all the indicators.

4.10.6 Mediating and Moderating Analysis

Mediation serves as an intervention that connects an exogenous construct to a certain endogenous construct. Bootstrapping was recommended for the examination of indirect effects (Preacher & Hayes, 2008), as it is a rigorous and reliable method of evaluating mediating effects (Hair, Sarstedt, et al., 2017; Hayes, 2009). In comparison to other statistical tests, bootstrapping does not constrain data distribution and performs well for models with simple or numerous mediators (Hair et al., 2014). Bootstrapping is completely compatible with PLS-SEM because they both do not rely on variables or sampling distribution. Therefore, swift guanxi, as the mediating variable in this study, was assessed using Preacher and Hayes' (2008) bootstrapping mediation analysis.

Following that, there are three ways to assess the moderating effect in PLS-SEM: (1) the product indicator approach (Chin et al., 2003), (2) the two-stage approach (Chin et al., 2003; Fassott et al., 2016), and (3) the orthogonalization approach (Little et al., 2006). Becker et al. (2018) concluded that the two-stage approach excelled over others in terms of moderating outcomes, particularly parameter recovery and statistical power. Furthermore, the two-stage approach generates interaction terms using latent variable scores, which is compatible with PLS-SEM modelling (Hair, Matthews, et al., 2017; Ramayah et al., 2016). Similarly, Henseler and Chin (2010) strongly recommend the use of the two-stage approach when the research model involves formative constructs. Thus, a two-stage approach was used to examine the moderating effects of PEEIM in this study. The importance of the moderating effect on explaining the endogenous construct was investigated further by examining its effect size (Chin et al., 2003; Hair, Matthews, et al., 2017). Lastly, an interaction plot was presented to visually show the direction of the significant interaction (Dawson, 2014).

4.11 Summary

This chapter presents an outline of the research design applied in this study, which guides the overall research process and data analysis. The researcher began by determining the target population and sampling technique, then estimated the sample size and designed the questionnaire. The target sample size for this study was set at 500 participants. Prior to data collection, pre-test, and pilot tests were performed to verify the questionnaire items' reliability and validity. The quota sampling technique was employed to gather data via an online survey. The measurement scales used in this study were adapted and modified from previous research. Finally, two software packages (SPSS v.26 and SmartPLS 4.0.9) were chosen for data analyses.

CHAPTER 5

FINDINGS AND ANALYSIS RESULTS

5.1 Introduction

The main purpose of this chapter is to present the results of the data analysis and evaluate the proposed hypotheses. This chapter is divided into twelve primary sections. After the introductory part, Section 5.2 details the data preparation process, encompassing data cleansing and the evaluation of CMV. Subsequently, Section 5.3 delves into the demographic characteristics of the respondents, while Section 5.4 illustrates the usage of live streaming commerce among respondents. Section 5.5 then showcases the outcomes of mean comparisons. Following this, Sections 5.6 through 5.9 provide a comprehensive presentation of the findings pertaining to the measurement model, descriptive analysis, and structural model. Sections 5.10 and 5.11 subsequently delve into the examination of mediation and moderation effects. Finally, an overview of the overall results of the hypotheses, along with a concise chapter summary, can be found in Sections 5.12 and 5.13.

5.2 Data Preparation

In this research, data was collected between 5th September and 4th October of 2023 from millennial shoppers who had live streaming shopping experience for at least three months on Douyin, Kuaishou, and Xiaohongshu. A total of 500 questionnaires were completed and returned. Subsequently, a sequence of data cleaning procedures, encompassing data screening and the evaluation of CMV, was executed to identify data input errors and potential biases before embarking on further analyses. These procedures are elucidated in the subsequent sub-sections.

5.2.1 Data Screening

Following the complete entry of data into the SPSS file, a series of data screening procedures were executed to check omission, completeness, and consistency (Zikmund et al., 2013). These screening steps were carried out within the SPSS software. Initially, a frequency test was applied to ascertain the absence of any missing values in the responses. Subsequently, a straight-lining evaluation using Microsoft Excel was conducted to identify participants who consistently provided identical responses for a majority of the questionnaire items. Fifty-four responses were excluded (through case-by-case deletion) due to the presence of apparent uniformity of answers (i.e., choosing the same option for all items). Consequently, 446 final responses were retained and employed for further analysis using SPSS 26 and SmartPLS 4.0.9. Further elaboration on the characteristics of the respondents is presented in Section 5.3.

5.2.2 Common Method Variance (CMV)

Recognising the potential for a single data source to introduce misleading connections between variables, it was essential to assess the presence of common method bias before proceeding with the examination of the proposed relationships. To address this concern, a statistical approach was employed. First, Harman's Single Factor Technique, as delineated by Podsakoff et al. (2003), was used to scrutinise the data. The results of the principal component factor analysis revealed that the first factor explained 31% of the variance, falling below the 40% threshold. This outcome, aligning with the insights of Babin et al. (2016), indicated that common method bias was not a significant issue in this study.

Subsequently, a full collinearity evaluation was performed to further assess the CMV, as recommended by Kock and Lynn (2012). This full collinearity assessment is recognised for generating more robust outcomes and is considered a more advanced approach compared to traditional post-hoc analyses (Kock & Lynn, 2012). The results presented in Table 5.1 displayed VIFs falling within the range of 1.018 to 1.387, all of which were below the critical threshold of 3.33 (Kock & Lynn, 2012). This reaffirmed that there were no substantial concerns related to CMV within this study.

Table 5.1 : Results of Full Collinearity Assessment

Latent Variable	Random Dummy Variable (VIF)
Expertise	1.387
Physical Attractiveness	1.189
Interaction Orientation	1.114
Media Richness	1.308
Personalisation	1.121
Mutual Understanding	1.292
Reciprocal favours	1.188
Relationship harmony	1.285
Purchase Intention	1.018
PEEIM	1.118

Note: VIF (Variance Inflation Factor)

5.3 Respondent Profile

This section discusses the demographic background of the respondents who participated in this study. A frequency test was performed to analyse the respondents' profiles, which included gender, age, education, monthly income, and occupation.

As exhibited in Table 5.2, there were 39.2% male respondents and 60.8% female respondents. The results showed that a majority of respondents were between 31 and 35 years old (40.8%), and had completed an undergraduate degree (76.90%), which is also consistent with related research (Gu et al., 2023). More than half of the respondents are employed by the private sector (59%), while one-third earn between RMB5,001 and RMB7,000 per month (31.8%).

The distribution of the sample of 446 respondents aligns with both previous research and China's online commerce statistics. First, despite live streaming commerce being considered a cross-gender universal shopping tool, a gender gap in the use of live streaming persists. Data from past research have suggested that female consumers lean towards using live streaming for shopping, while male consumers tend to prefer it for gaming (iiMedia, 2023; Lu & Chen, 2021). Second, data from O'Ratings (2021) indicate that live streaming shopping is not confined to young people but has become part of the lifestyle of China's core group. The age distribution of core consumer power users of live streaming shopping falls within the 30-39 age range. A report by iiMedia (2023) underscores that college and undergraduate users constitute the highest proportion of live streaming users in China. Lastly, occupational and income distribution also align with findings from earlier studies (e.g., Chen et al., 2021; Lu & Chen, 2021).

Table 5.2 : Respondent Profile

Category	Item	Frequency (n=446)	Percentage (%)
Gender	Male	175	39.2%
	Female	271	60.8%
Age	27-30 years old	157	35.2%
	31-35 years old	182	40.8%
	36-42 years old	107	24.0%
Highest Degree (Earned)	Second school or below	12	2.7%
	Junior college	101	22.6%
	Undergraduate degree	271	60.8%
	Graduate Degree	53	11.9%
	Postgraduate degree	9	2.0%
Occupation	Employee- Government sector	122	27.4%
	Employee - Private sector	263	59.0%
	Self-employed	24	5.4%
	Student	18	4.0%
	Others	19	4.3%
Monthly income	Below RMB 3000	7	1.6%
	RMB 3001–5000	43	9.6%
	RMB 5001–7000	142	31.8%
	RMB 7001–9000	106	23.8%
	RMB 9001–11000	72	16.1%
	RMB 11001–13000	41	9.2%
	RMB 13001–15000	19	4.3%
	RMB 15001 and above	16	3.6%

5.4 Respondents' Live Streaming Commerce Usage

The survey began with screening questions designed to determine whether respondents had any prior experience with live streaming shopping on the three specified platforms (Douyin, Kuaishou, Xiaohongshu) for a minimum of three months. Only individuals who answered "YES" were permitted to continue with the survey. These participants were then instructed to evaluate the items in relation to their favoured live streaming commerce platform. The characteristics of live streaming commerce shopping for the 446 surveyed participants are described as follows.

As the study used quota sampling based on the number of active users on each platform, respondents preferred live streaming commerce platforms were 238 for Douyin, 140 for Kuaishou, and 68 for Xiaoshoushu, respectively. Regarding product categories purchased by millennial shoppers on their preferred live streaming commerce platform, the majority (76.01%) opted for apparel, making it the most popular category. Following closely behind were cosmetics (63.45%), daily household items (57.17%), food and health products (56.73%), and sports and travel-related items (22.87%) (see Table 5.3).

Table 5.3 : Products Purchased (by Category)

Product Category	Frequency	Percentage of Cases (%)
Apparel	339	76.01%
Cosmetics	283	63.45%
Daily Household	255	57.17%
Food & Health	253	56.73%
Sports & Travel	102	22.87%
Books & Audio	61	13.68%
Electronic	53	11.88%
Maternal & Child	35	7.85%
Jewelry	16	3.59%

As indicated in Table 5.4, the majority of participants (27.60%) had live streaming shopping experience spanning 13 to 18 months. Approximately 23% of respondents had engaged in live streaming commerce for 19 to 24 months, while 20% had a shopping history of 7 to 12 months. Another 20.9% had utilised live streaming commerce for over two years. The remaining participants, constituting 7.80%, had engaged in live streaming shopping for at least six months (see Table 5.4 for details).

Regarding the frequency of purchases on their preferred live streaming commerce platform, the majority of participants (34.8%) indicated a weekly buying pattern.

Other respondents reported their shopping app frequency as "monthly" (21.5%), "once every 2 to 3 months" (18.2%), "daily" (11.7%), "once a year or less" (9.4%), and "once every four to six months" (4.5%) (refer to Table 5.4).

Table 5.4 : Length and Frequency of Live Streaming Commerce Usage

Category	Description	Frequency	Percentage (%)
Live streaming shopping experience	3-6 months	35	7.8%
	7-12 months	91	20.4%
	13-18 months	123	27.6%
	19-24 months	104	23.3%
	More than 2 years	93	20.9%
Live streaming shopping frequency	Daily	52	11.7%
	Weekly	155	34.8%
	Monthly	96	21.5%
	Once every 2-3 months	81	18.2%
	Once every 4-6 months	20	4.5%
	Once a year or less	42	9.4%

5.5 The Impact of Demographic Factors on Dependent Variables

This section investigates the potential influence of demographic factors on purchase intention. The PLS algorithm and bootstrapping method were utilised to evaluate the strength and significance of the connection between these demographic factors and the dependent variables.

As depicted in Table 5.5, the findings reveal that gender, age, educational background, occupation, and monthly income had minimal effects on purchase intention. This is substantiated by p-values exceeding 0.05, indicating that these demographic factors did not exert a significant influence on the analysis outcomes.

Table 5.5 : Demographic Impact on Dependent Variables

Path Relationship	Std. Beta	Std. Error	t-value	p-value	CI (2.5%, 97.5%)
Gender -> PI	-0.112	0.067	1.677	0.094	(-0.241, 0.016)
Age -> PI	-0.027	0.035	0.774	0.439	(-0.09, 0.045)
Education -> PI	-0.006	0.031	0.19	0.849	(-0.068, 0.053)
Career -> PI	0.02	0.036	0.563	0.574	(-0.052, 0.09)
Income -> PI	-0.024	0.033	0.722	0.47	(-0.088, 0.04)

5.6 Reflective Measurement Model

To assess the measurement model, an extensive set of tests was carried out, encompassing evaluations of internal consistency (Cronbach's alpha and composite reliability), convergent validity (outer loading and composite reliability), and discriminant validity (HTMT). The detailed findings of the measurement model are provided in the subsequent sections.

5.6.1 Internal Consistency and Convergent Validity

First, this study assessed the internal consistency of items by examining both CR and Cronbach's alpha (α). As outlined in Table 5.6, all α values fell within the range of 0.578 to 0.898, and CR values spanned from 0.780 to 0.937. Notably, these values largely surpassed the recommended threshold of 0.70 (Hair et al., 2019), signalling that the constructs in this research met the requirement for internal consistency.

Next, this research assessed the convergent validity of the constructs through the analysis of outer loadings and AVE values. As shown in Table 5.6, each item met the recommended outer loading criterion, ranging from 0.604 to 0.930, except for EOP2, EOP5, and PA4, which fell below the accepted threshold of 0.50 (Bagozzi et al., 1991; Hair, Sarstedt, et al., 2017). Consequently, these three items were excluded. On the other hand, all constructs demonstrated AVE scores surpassing the minimum threshold of 0.50 (Bagozzi & Yi, 1988; Fornell & Larcker, 1981). This confirms that all items significantly contributed to their respective constructs, explaining more than half of the constructs' variance (Hair et al., 2019), thus establishing convergent validity.

Table 5.6 : Assessment of Reliability and Convergent Validity

Construct	Item	Loading	Cronbach's alpha	CR	AVE
Expertise	EXP1	0.842	0.786	0.863	0.613
	EXP2	0.822			
	EXP3	0.798			
	EXP4	0.655			
Physical Attractiveness	ATT1	0.818	0.784	0.874	0.698
	ATT2	0.817			
	ATT3	0.87			
Interaction Orientation	INO1	0.799	0.851	0.889	0.545
	INO2	0.796			
	INO3	0.807			
	INO4	0.77			
	INO5	0.776			
	INO6	D			
	INO7	0.761			
Media Richness	MR1	0.804	0.821	0.882	0.651
	MR2	0.802			
	MR3	0.8			
	MR4	0.82			
Personalisation	PER1	0.863	0.829	0.897	0.743
	PER2	0.858			
	PER3	0.864			
Swift guanxi (Mutual Understanding)	MUT1	0.827	0.856	0.897	0.635
	MUT2	0.809			
	MUT3	0.814			
	MUT4	0.786			
	MUT5	0.745			
Swift guanxi (Reciprocal Favours)	RF1	0.683	0.787	0.875	0.7
	RF2	0.815			
	RF3	0.828			
	RF4	0.798			
Swift guanxi (Relationship Harmony)	RH1	0.869	0.788	0.863	0.613
	RH2	0.793			
	RH3	0.846			
Purchase Intention	PI1	0.849	0.792	0.878	0.706
	PI2	0.855			
	PI3	0.816			
PEEIM	PEEIM1	0.84	0.8	0.882	0.714
	PEEIM2	0.855			
	PEEIM3	0.84			

Note: D=Item deleted due to low outer loading; CR (Composite Reliability); AVE (Average Variance Extracted)

5.6.2 Discriminant Validity

As outlined by Hair et al. (2017), assessing discriminant validity is crucial for identifying potential overlaps among constructs. In this research, Henseler's HTMT ratio of correlation was utilised to assess discriminant validity. As indicated by Table 5.7, all HTMT values were below the conservative criterion of 0.85 (Kline, 2015), demonstrating satisfactory discriminant validity.

Table 5.7 : Discriminant Validity (HTMT Criterion)

	1	2	3	4	5	6	7	8	9	10
1. Attractiveness										
2. Expertise	0.523									
3. Interaction Orientation	0.479	0.482								
4. Media Richness	0.428	0.425	0.585							
5. Mutual Understanding	0.548	0.594	0.527	0.526						
6. PEEIM	0.329	0.357	0.266	0.207	0.456					
7. Personalisation	0.307	0.292	0.396	0.345	0.33	0.258				
8. Purchase Intention	0.557	0.660	0.642	0.567	0.706	0.398	0.45			
9.Reciprocal Favours	0.534	0.572	0.657	0.555	0.745	0.495	0.373	0.712		
10. Relationship Harmony	0.473	0.589	0.552	0.538	0.604	0.234	0.163	0.678	0.698	

Note: HTMT < 0.85

5.7 Higher-Order Construct (HOC)

This study approached swift guanxi as reflective-formative HOCs. The two-stage approach (Becker et al., 2012; Ringle et al., 2012; Sarstedt et al., 2019) was employed to assess the HOCs. Initially, the LOCs were evaluated using a standard reflective measurement model (discussed in the previous section). In the subsequent stage, the assessment of HOCs was conducted through formative measurement model procedures, encompassing checks for convergent validity, collinearity issues, and indicators' outer weight and significance.

In the evaluation of the formative measurement model, this study examined the convergent validity of the HOC using a single global item, as recommended by Cheah et al. (2018). For swift guanxi, the global item ("Overall, I quickly formed an interpersonal guanxi with streamer") was formulated. The results of the redundancy analysis demonstrates that the global item yielded a path coefficient of 0.742. This suggested that three lower constructs can explain more than 50 percent of the variance of swift guanxi.

Next, this study examined the collinearity issues among the LOCs. Table 5.8 demonstrates that all VIF values ranged from 1.012 to 1.669, which were below the threshold of 3.0, indicating that collinearity was not a critical issue.

Finally, this study assessed the outer weights and the significance through bootstrapping 5000 subsamples (Cheah et al., 2018; Hair, Sarstedt, et al., 2017). The findings revealed that all three LOCs (mutual understanding = 0.337; reciprocal favours = 0.400; relationship harmony = 0.454;) exhibited significant effects on swift guanxi ($p < 0.05$). In conclusion, these results align with existing literature, reinforcing the notion that swift guanxi is formatively shaped by three LOCs.

Table 5.8 : Assessment of Higher-Order Construct

Second-order constructs	First-order construct	Convergent validity	OuterVIFs	Outer weights	Std. error	*t*-value	*p*-value
Swift guanxi	Mutual understanding	0.742	1.708	0.337	0.054	6.247	0.000
	Reciprocal favours		1.852	0.400	0.060	6.722	0.000
	Relationship harmony		1.539	0.454	0.059	7.668	0.000

Note: VIF (Variance Inflation Factor)

5.8 Descriptive and Multivariate Normality Analyses

To comprehend participant responses to each construct, this study analysed the mean and standard deviation for each construct. As described by Bougie and Sekaran (2013), the mean signifies the data's central tendency, while the standard deviation illustrates data variation. Table 5.9 exhibits the means and deviations for the nine constructs within this study.

In this research, participants perceived the streamers on live streaming commerce platforms as having high expertise (Mean = 3.899, SD = 0.577), physical attractiveness (Mean = 3.880, SD = 0.661), and interaction orientation (Mean = 3.817, SD = 0.648), with interaction orientation being the most popular streamer trait. Regarding technical aspects, respondents acknowledged the presence of media richness (Mean = 3.899, SD = 0.652) and personalisation (Mean = 3.684, SD = 0.806) in live streaming platforms.

The swift guanxi construct involved three primary sub-dimensions: mutual understanding (Mean = 3.622, SD= 0.681), reciprocity (Mean = 3.501, SD = 0.705), and relationship harmony (Mean = 3.895, SD = 0.647). Participants indicated the establishment of interpersonal connections with some streamers.

Additionally, the results on purchase intention revealed a strong inclination among respondents to make purchases from streamers on their preferred live streaming commerce platform (Mean = 4.019, SD = 0.586). Finally, respondents perceived a high PEEIM (Mean = 3.658, SD = 0.768) on their preferred live streaming commerce platform.

The assessment of multivariate normality using Mardia's coefficient indicated that the kurtosis (b = 173.87) surpassed the threshold of 20, suggesting non-normal data distribution (Kline, 2015). Consequently, PLS-SEM emerged as the most suitable technique for this study. Previous studies have emphasised that PLS-SEM is more adept at handling non-normally distributed data and is less strict regarding data distribution (Hair, Matthews, et al., 2017).

Table 5.9 : Results of Descriptive Analysis

Construct	No of Items	Mean	Standard Deviation
1. Expertise	4	3.899	0.577
2. Physical Attractiveness	3	3.880	0.661
3. Interaction Orientation	6	3.817	0.648
4. Media Richness	4	3.899	0.652
5. Personalisation	3	3.684	0.806
6. Swift guanxi			
• Mutual Understanding	5	3.622	0.681
• Reciprocal favours	4	3.501	0.705
• Relationship harmony	3	3.895	0.647
7. Purchase Intention	3	4.019	0.586
8. PEEIM	3	3.658	0.768
• Normality Test: Mardia's Multivariate Kurtosis → b = 173.87			

5.9 Structural Model

This section exhibits the outcomes of the evaluation of the structural model. The data collected was analysed using a five-step process, each step of which is described in detail in the subsequent subsections (refer to Table 5.10).

5.9.1 Collinearity Assessment

Researchers should identify collinearity issues early in structural model assessment to ensure accurate or unbiased results (Hair, Risher, et al., 2019). This study employed the VIF to evaluate collinearity among exogenous constructs. As indicated in Table 5.10, the VIF values for all exogenous constructs ranged between 1.184 and 2.155, which is below the criterion of 3.3 (Becker et al., 2012; Hair, Risher, et al., 2019), suggesting that multicollinearity was not a concern in this research.

5.9.2 Path Coefficient Assessment

The second step aims to assess the statistical significance and relevance of the path coefficients of the proposed hypotheses outlined in Chapter Three. Utilising the bootstrapping technique with 5000 subsamples (Streukens & Leroi-Werelds, 2016), 11 hypotheses were evaluated, with eight showing a t-value >1.645, indicating significance at the 0.05 level (refer to Table 5.10).

Firstly, the effects of three streamer characteristics and two technical characteristics on purchase intentions were assessed. As predicted, streamer expertise ($\beta = 0.163$, t-value = 3.596, p-value < 0.001) and interaction orientation ($\beta = 0.131$, t-value = 2.409, p-value = 0.016) led to stronger purchase intentions, which provided support for H1a and H1c. However, contrary to previous predictions, the results indicated that the physical attractiveness (β = 0.059, t-value = 1.267, p-value = 0.205) of the streamer was not significantly related to purchase intention. Therefore, H1b was not supported. Among the technical characteristics of the platform, media richness had no significant relationship with purchase intention (β = 0.072, t-value = 1.373, p-value = 0.141). Thus, H1d was not supported. As predicted, hypothesis H1e was supported as personalisation was found to have a significant positive effect on purchase intention (β = 0.135, t-value = 2.788, p-value = 0.005).

Secondly, the relationship between swift guanxi and purchase intention was analysed. The result showed that swift guanxi had a significant positive relationship with purchase intention (β = 0.401, t-value = 7.134, p-value < 0.001). Thus, H2 was supported.

Lastly, the impact of three streamer characteristics and two technical characteristics on swift guanxi were examined. The findings indicated that streamer expertise (β = 0.291, t-value = 6.866, p-value< 0.001), attractiveness (β = 0.187, t-value = 3.190, p-value = 0.001), interaction orientation (β = 0.261, t-value = 5.003, p-value < 0.001), and media richness of the platform (β = 0.224, t-value = 4.707, p-value < 0.001) had a strong positive effect on swift guanxi. Thus, H2a, H2b, H2c, and H2d were supported. However, there was no significant relationship between personalisation and swift guanxi (β = 0.2, t = 0.444, p = 0.657). Therefore, H4b was not supported.

5.9.3 Coefficient of Determination (R^2)

The third step was to evaluate the explanatory power, i.e. coefficient of determination (R^2), of the endogenous constructs (swift guanxi and purchase intention). As shown in Table 5.10, the model can explain 53.3% of the variance (R^2) for swift guanxi and 53.8% of the variance (R^2) for purchase intention, indicating that both endogenous constructs gained large explanatory power (Cohen, 1988).

5.9.4 Effect Size (f^2)

This study interpreted effect size findings (f^2) in line with Cohen's (1988) benchmarks, where 0.02, 0.15, and 0.35 represent small, medium, and large effect sizes of exogenous variables on an endogenous variable. As shown in Table 5.10, swift guanxi ($f^2 = 0.161$) was the most significant predictor of purchase intention with a medium effect size, while expertise ($f^2 = 0.037$), interaction orientation ($f^2 = 0.021$), and personalisation ($f^2 = 0.033$) exhibited small effect sizes. Conversely, attractiveness ($f^2 = 0.005$) and media richness ($f^2 = 0.007$) showed merely trivial effect sizes.

Additionally, in explaining swift guanxi, expertise ($f^2 = 0.134$), attractiveness ($f^2 = 0.055$), interaction orientation ($f^2 = 0.090$), and media richness ($f^2 = 0.075$) showed small effect sizes (refer to Table 5.10). Notably, personalisation ($f^2 = 0.001$) displayed trivial effect sizes.

5.9.5 Predictive Relevance (Q^2 and PLSpredict)

The last step was to assess predictive relevance through Stone-Geisser's Q^2 (Geisser, 1974; Stone, 1974). Employing the blindfolding procedure, the analysis revealed that both swift guanxi (0.37) and purchase intention (0.36) had Q^2 values exceeding zero (refer to Table 5.10), signifying the model's predictive relevance.

The PLSpredict technique developed by Shmueli et al. (2016, 2019) was used to further evaluate the predictive relevance of the endogenous constructs (i.e. swift guanxi and purchase intention). As demonstrated in Table 5.11, the PLS-SEM model demonstrated lower prediction errors (RMSE and MAE) for all item values of swift guanxi and purchase intention compared to the linear model. Therefore, swift guanxi and purchase intention demonstrated a large predictive power (Shmueli et al., 2019). The predictions results highlight the relevance of the socio-technical theory (Bostrom & Heinen, 1977) in studying purchase intentions for live streaming commerce. In this case, streamer attributes (i.e., expertise, physical attractiveness, and interaction orientation) and technical attributes (i.e., media richness and personalisation) emerged as vital antecedents to purchase intentions in live streaming commerce.

Table 5.10 : Results of the Structural Model

Path Relationship	Std. Beta	SE	Confidence Interval	*t*-value	*p*-value	VIF	f^2	R^2	Q^2
H1a: Expertise → Purchase intention	0.163	0.045	(0.074, 0.251)	3.596	0.000	1.567	0.037	0.538	0.36
H1b: Attractiveness → Purchase intention	0.059	0.047	(-0.028, 0.155)	1.267	0.205	1.432	0.005		
H1c: Interaction orientation → Purchase intention	0.131	0.054	(0.022, 0.238)	2.409	0.016	1.793	0.021		
H1d: Media richness → Purchase intention	0.072	0.049	(-0.022, 0.171)	1.473	0.141	1.581	0.007		
H1e: Personalisation → Purchase intention	0.135	0.048	(0.04, 0.233)	2.788	0.005	1.184	0.033		
H2: Swift guanxi → Purchase intention	0.401	0.056	(0.292, 0.509)	7.134	0.000	2.155	0.161		
H3a: Expertise → Swift guanxi	0.291	0.042	(0.204, 0.37)	6.866	0.000	1.353	0.134	0.533	0.37
H3b: Attractiveness → Swift guanxi	0.187	0.059	(0.077, 0.304)	3.19	0.001	1.352	0.055		
H3c: Interaction orientation → Swift guanxi	0.261	0.052	(0.154, 0.36)	5.003	0.000	1.623	0.09		
H3d: Media richness → Swift guanxi	0.224	0.048	(0.129, 0.32)	4.707	0.000	1.433	0.075		
H3e: Personalisation → Swift guanxi	0.020	0.044	(-0.06, 0.112)	0.444	0.657	1.173	0.001		

Table 5.11 : Assessment of PLS Predict

		PLS		LM		PLS-LM		
	Q^2predict	RMSE	MAE	RMSE	MAE	RMSE	MAE	Predictive power
MU	0.363	0.800	0.622	0.818	0.631	-0.018	-0.009	Large
RF	0.381	0.789	0.613	0.809	0.624	-0.020	-0.011	
RH	0.333	0.820	0.617	0.837	0.636	-0.017	-0.019	
PI1	0.303	0.575	0.453	0.581	0.448	-0.006	0.005	Medium
PI2	0.331	0.641	0.510	0.655	0.514	-0.014	-0.004	
PI3	0.243	0.729	0.582	0.745	0.594	-0.016	-0.012	

Note: MU (mutual understanding); RF (reciprocal favours); RH (relationship harmony); PI (purchase intention); RMSE (Root mean squared error); MAE (Mean absolute error)

5.10 Mediation Effect

This study also proposed mediation paths between streamer attributes-purchase intention and technical attributes-purchase intention via swift guanxi (H4a-H4e). According to the bootstrap estimation with 5000 sub-samples (Preacher & Hayes, 2008), the mediation effect of swift guanxi between expertise and purchase intention was significant (β = 0.117, t-value = 4.700, p-value < 0.001, CI = 0.070, 0.169). Similarly, swift guanxi was found to mediate the relationship between attractiveness and purchase intention (β = 0.075, t-value = 3.083, p-value < 0.05, CI = 0.030, 0.125). It was also found that swift guanxi significantly mediated the relationship between interaction orientation and purchase intention (β = 0.105, t-value = 3.876, p-value < 0.001, CI = 0.056, 0.162). Besides, swift guanxi exerted mediating effect between media richness and purchase intention (β = 0.090, t-value = 3.656, p-value < 0.001, CI = 0.046, 0.143). There was no mediating effect of swift guanxi in the relationship between personalisation and purchase intention. Accordingly, H4e was not supported while H4a, H4b, H4c and H4d were supported (see Table 5.12).

Table 5.12 : Assessment of Mediating Effect

Path Relationship	Std. Beta	Std. Error	*t*-value	*p*-value	Confidence Interval	Full or Partial
H4a: EXP → SW→ PI	0.117	0.025	4.700	0.000	(0.070, 0.169)	Partial
H4b: ATT→ SW→ PI	0.075	0.024	3.082	0.002	(0.030, 0.125)	Full
H4c: INO → SW → PI	0.105	0.027	3.876	0.000	(0.056, 0.162)	Partial
H4d: MR → SW → PI	0.090	0.025	3.656	0.000	(0.046, 0.143)	Full
H3e: PER → SW → PI	0.008	0.018	0.444	0.657	(-0.025, 0.045)	Not

Note: EXP (Expertise); ATT (Physical Attractiveness); INO (Interaction Orientation); MR (Media Richness); PER (Personalisation); SW (Swift Guanxi); PI (Purchase Intention)

5.11 Moderation Effect

The moderation effect was examined using a two-stage approach. Initially, the R^2 values were compared between the main model and the interaction model using the PLS algorithm. The endogenous variable, purchase intention, exhibited an R^2 of 0.538 in the main model. With the introduction of PEEIM (R^2=0.561, increase of 0.023) as moderators, these values improved. Subsequently, employing the bootstrapping technique with 5000 sub-samples (Table 5.13), the latent interaction technique revealed that PEEIM significantly influenced swift guanxi and purchase intention (β=0.146, t-value=4.436, p-value<0.001), supporting H5.

This outcome was further depicted using an interaction plot (Dawson, 2014), illustrating a stronger positive relationship between swift guanxi and purchase intention for the high PEEIM groups compared to their respective low groups (Figure 5.1), confirming support for H5. Additionally, the effect size (f^2) of PEEIM was 0.066, emphasising the relevance of PEEIM as moderators (Chin et al., 2003).

Table 5.13 : Results of Moderating Effect

Path Relationship	Std. Beta	Std. Error	*t*-value	*p*-value	Confidence Interval
H5: PEEIM * SW → PI	0.146	0.033	4.436	0.000	(0.073, 0.206)

Note: SW (Swift Guanxi); PI (Purchase Intention)

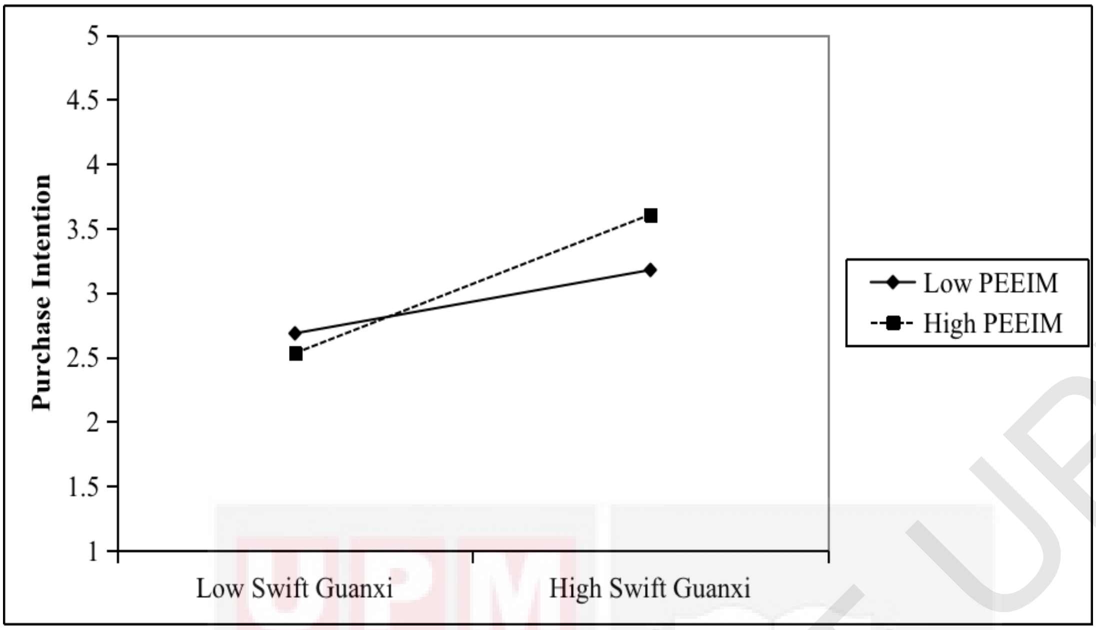

Figure 5.1 : Swift Guanxi*PEEIM on Purchase Intention

5.12 Overall Hypotheses

The PLS-SEM technique was used to test the eighteen hypotheses outlined in Chapter Three. The bootstrapping analysis revealed that most of the proposed hypotheses were supported, except for H1b, H1d, H3e and H4e. Table 5.14 provides an overview of the hypotheses outcomes, whereas Figure 5.2 illustrates the path results.

Table 5.14 : Summary of Hypotheses Results

Path	Hypothesis Statement	Result
H1a	Expertise is positively related to purchase intention in live streaming shopping among millennial shoppers.	Support
H1b	Attractiveness is positively related to purchase intention in live streaming shopping among millennial shoppers.	Not Support
H1c	Interaction orientation is positively related to purchase intention in live streaming shopping among millennial shoppers.	Support
H1d	Media richness is positively related to purchase intention in live streaming shopping among millennial shoppers.	Not Support
H1e	Personalisation is positively related to purchase intention in live streaming shopping among millennial shoppers.	Support
H2	Swift guanxi is positively related to purchase intention in live streaming shopping among millennial shoppers.	Support
H3a	Expertise is positively related to swift guanxi in live streaming shopping among millennial shoppers.	Support
H3b	Attractiveness is positively related to swift guanxi in live streaming shopping among millennial shoppers.	Support
H3c	Interaction orientation is positively related to swift guanxi in live streaming shopping among millennial shoppers.	Support
H3d	Media richness is positively related to swift guanxi in live streaming shopping among millennial shoppers.	Support
H3e	Personalisation is positively related to swift guanxi in live streaming shopping among millennial shoppers.	Not Support
H4a	Swift guanxi mediates the relationship between expertise and purchase intention in live streaming shopping among millennial shoppers.	Support
H4b	Swift guanxi mediates the relationship between attractiveness and purchase intention in live streaming shopping among millennial shoppers.	Support
H4c	Swift guanxi mediates the relationship between interaction orientation and purchase intention in live streaming shopping among millennial shoppers.	Support
H4d	Swift guanxi mediates the relationship between media richness and purchase intention in live streaming shopping among millennial shoppers.	Support
H4e	Swift guanxi mediates the relationship between personalisation and purchase intention in live streaming shopping among millennial shoppers.	Not Support
H5	PEEIM positively significantly moderates the relationship between swift guanxi and purchase intention in live streaming shopping, where the relationship is stronger when PEEIM is high among millennial shoppers.	Support

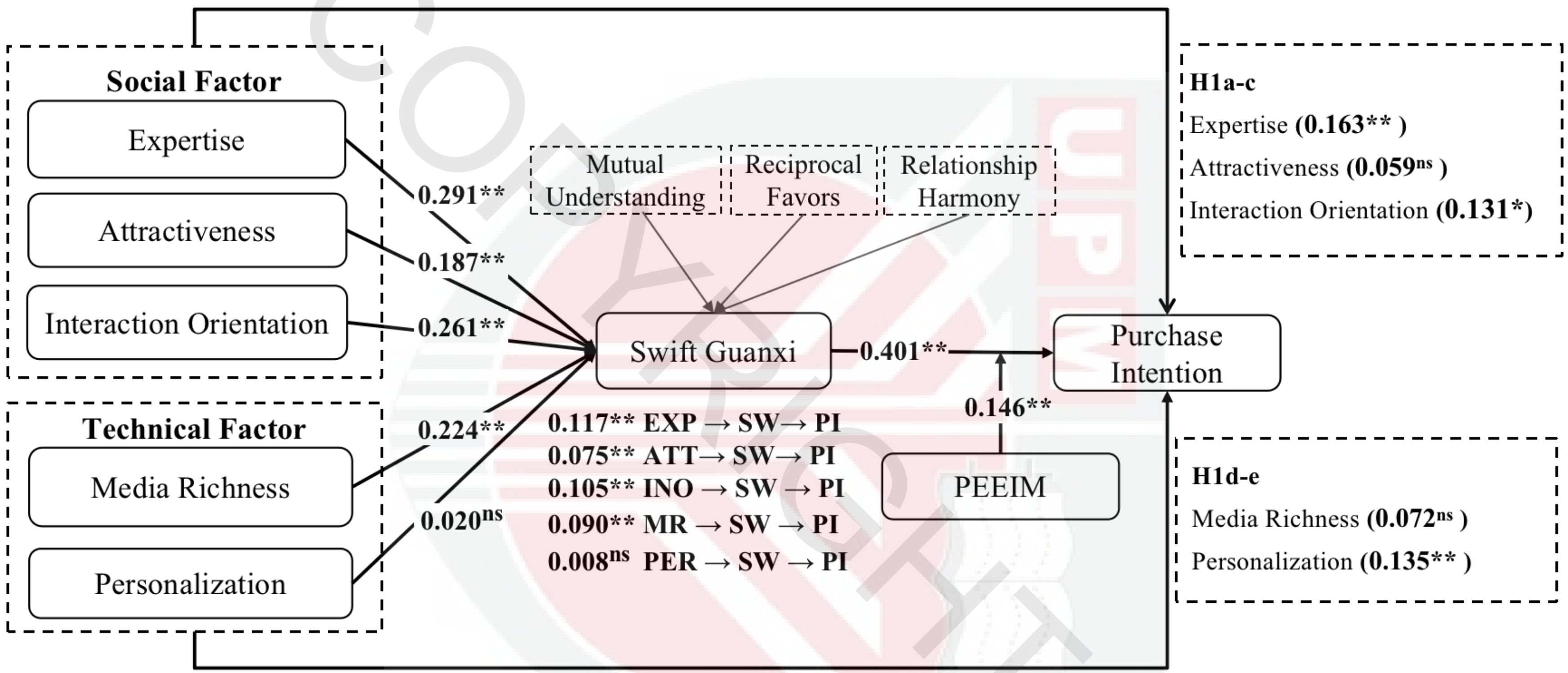

Figure 5.2 : Final Research Model with Path Coefficient Result

Note: *p < 0.05; **p < 0.01; EXP (Expertise); ATT (Physical Attractiveness); INO (Interaction Orientation); MR (Media Richness); PER (Personalisation); SW (Swift Guanxi); PI (Purchase Intention)

5.13 Summary

In this chapter, the outcomes of the data analysis were detailed. Several data preparation steps were executed, leading to the exclusion of 54 questionnaires due to consistent responses. Consequently, 446 complete responses formed the basis of the study. Utilising the SmartPLS software (version 4.0.9), both the measurement and structural models were evaluated. In summary, the findings indicated support for fifteen out of eighteen proposed relationships (H1a, H1c, H1e, H2, H3a-H3d, H4a-H4d, and H5), while H1b, H1d, H3e, and H4e did not receive support. The subsequent chapter delves into these results, elucidating the study's theoretical and managerial contributions and limitations, and providing guidance for future research.

CHAPTER 6

DISCUSSION AND CONCLUSION

6.1 Introduction

This final chapter discusses the results derived from Chapter Five. This chapter is divided into five main sections. The first section provides a discussion of the major findings in response to the research questions presented in Chapter One. The second and third sections outline the theoretical and managerial contributions of the study. Subsequently, limitations and future research directions are presented. Finally, concluding remarks end this thesis.

6.2 Discussion of Major Findings

This study developed and empirically examined a model to understand the determinants influencing millennial shoppers' purchase intention in live streaming commerce. In particular, the present study extended the socio-technical theory (Trist et al., 1963) to comprehend the factors that motivate users' live streaming commerce purchase intention in the context of China. Responding to Ma et al.'s (2021) call, streamer attributes and technical attributes were suggested as the social and technical factors, respectively, that drive live streaming commerce purchase intention. Following the logic of the S-O-R model (Mehrabian & Russell, 1974), this study posited swift guanxi as a mediator in elucidating purchase intention. In addition, the boundary condition (i.e., PEEIM) affecting the relationship between swift guanxi and purchase intention was identified. Based on data from 446 millennial shoppers, the present study found the following:

(1) Streamer expertise, interaction orientation, and personalisation were positively related to purchase intention towards live streaming commerce, while streamer attractiveness and media richness were not. That is, when users interact with expertise and interaction-orientated streamers, they are more likely to have purchase intention. Meanwhile, a personalised platform can effectively enhance live streaming commerce purchase intention among millennial mobile shoppers.

(2) Swift guanxi is positively impacted by streamer expertise, attractiveness interaction orientation, and media richness. This study also supports the mediating effect of swift guanxi between the study's antecedents (expertise, attractiveness interaction orientation, and media richness) and outcome (purchase intention). This finding adds value to the existing literature by revealing the importance of swift guanxi in the effort to convert viewers to shoppers.

(3) PEEIM moderates the path between swift guanxi and purchase intention. The positive association between swift guanxi and purchase intention was stronger when users had higher PEEIM. This underscores the significance of improving PEEIM in live streaming shopping, as neglecting this aspect may hinder swift guanxi and their purchase intention.

6.2.1 Discussion of Antecedents to Purchase Intention

The first part of this study aimed to elucidate the features that encourage live streaming commerce purchase intention. Drawing from the socio-technical theory (Trist et al., 1963), the present study postulated that streamer attributes (i.e., expertise, attractiveness, and interaction orientation) and technical attributes (i.e., media richness and personalisation) were social and technical factors that drive live streaming commerce purchase intention.

This study indicates that a majority of streamers' attributes show a significant positive correlation with viewers' purchase intention. This finding is consistent with prior research emphasising the crucial role of streamers' attributes as key social factors contributing to the success of live streaming commerce (Guo et al., 2022). Notably, streamer expertise demonstrated the most significant path coefficient, highlighting the importance of expertise in the realm of live streaming commerce. This finding aligns with earlier studies (Hovland et al., 1953; Wiedmann & von Mettenheim, 2020), suggesting that expertise is a paramount attribute for communicators in influencing others' attitudes. In the context of live streaming commerce, where streamers serve as the primary source of information, their professional explanations and demonstrations can enhance consumers' understanding of a product, consequently stimulating their purchase intention.

Contrary to earlier predictions, this study found that attractiveness does not have a significant direct impact on purchase intention. Nevertheless, it is important to note that attractiveness does exert an indirect influence on purchase intention through the concept of swift guanxi. The insignificance between physical attractiveness and purchase intention can be explained by the fact that the streamers are beautiful but not related to the product (Park & Lin, 2020; Sokolova & Kefi, 2022). Meanwhile, although attractive streamers do not directly drive users' purchase intentions, they still capture the viewer's attention. In addition, this unexpected finding may be attributed to the widespread attractiveness of streamers in the current landscape. In a saturated beauty environment, the halo effect associated with attractiveness appears to diminish (Chetioui et al., 2022; Sokolova & Kefi, 2022). Another possible explanation is related to the weakened institutional system on social media platforms, prompting users to become more discerning in their purchasing decisions (Fan et al., 2019; Lin et al., 2019). In such instances, the study suggests that attractiveness alone lacks sufficient strength to directly impact purchase intention. Besides that, the insignificant direct effect could be attributed to a biased sample composition that was skewed towards females (60.80%). Research has established that females may experience "same-sex envy" toward female streamers, while female streamers account for almost 70% of the total streamers (Fisher & Cox, 2011; iiMedia, 2022; Liu et al., 2009). Therefore, this could be another reason attractiveness did not significantly influence the purchase intention in this study.

Moreover, this study proved that the interaction orientation exerts a positive impact on purchase intention. This finding confirms previous literature (Liao et al., 2022), suggesting that streamers' friendly and helpful attitudes can be influential in an individual's decision-making process. Since the hallmark of live streaming commerce lies in the interaction between the streamer and viewers, interaction-oriented streamers engage actively with their audience and offer assistance. As a reciprocal return, viewers actively interact with the streamer and exhibit positive behaviours, such as purchase intention.

In addition, contrary to the initial hypothesis, media richness did not significantly predict purchase intention directly. However, this finding resonates with the results of recent studies in which the researchers found that media richness only generates positive behaviours through the mediation of satisfaction, interpersonal relationships (Zhang et al., 2023), and positive emotions (Li & Meshkova, 2013; Tong et al., 2022). In addition, previous 06/03/2025 08:22:00research showed that media richness has a direct positive effect on purchase intention only when users establish trust with online auction sellers (Chen et al., 2016), whereas the report indicates that 82.9% of users lack trust in live streaming commerce sellers due to exaggerated content and counterfeit goods (China Youth Daily, 2022). Another possible explanation is that there is a general similarity in functionality across live streaming platforms, where media richness is seen as an essential feature of the platform, thus making it less effective in shaping users' purchase intention.

Finally, personalisation was found to have a significant relationship with purchase intention. This is congruent with previous studies, which revealed that personalisation results in benefits received and generate higher purchase intention (Pappas et al., 2014, 2017). The result produced evidence that personalised content is better than routine content that neglects an individual’s specific needs (Tam & Ho, 2006), thereby delivering higher purchase intention. In live streaming commerce, providing customers with personalised services, such as recommending products that may satisfy viewers' desires based on the user's browser history, can increase purchase intention as their needs and desires are met accordingly (Chandra et al., 2022).

In conclusion, the social and technical characteristics of live streaming commerce, encompassing streamer expertise, streamer interaction orientation, and platform personalisation, are excellent strategies for meeting the needs of millennial live streaming commerce users and ultimately building purchase intention.

6.2.2 Discussion of Antecedents and Effect of Swift Guanxi

Unlike relationship marketing in Western markets, China emphasises guanxi. As an extension of traditional guanxi in the online marketplace, swift guanxi is also becoming increasingly important in Chinese online markets as consumers want to spend much time and effort to form relationships (Ou, Pavlou, & Davison, 2014). In fact, swift guanxi is considered as one of the most effective strategies for motivating positive consumer behaviour in China.

This study provides empirical evidence to confirm the role of streamer attributes (e.g., expertise, attractiveness, and interaction orientation) in heightening swift guanxi. Live streaming commerce enables users to watch the streamers' gestures and voices and interact in real-time, like offline. Therefore, positive streamer attributes also play a significant role in shaping relationship quality (e.g., swift guanxi) between streamers and users. Notably, streamer expertise exhibited the strongest path coefficient, underscoring the significance of expertise in live streaming commerce. This corroborates the findings of previous studies that streamers with professional knowledge are capable of offering appropriate suggestions for their customers and reduce information asymmetry, leading to richer and deeper online relationships (Chen et al., 2021; Zhou et al., 2022). Furthermore, attractiveness was found to be a significant predictor of swift guanxi. This corroborates previous findings that attractiveness is an essential condition for building relationships (GIFFIN, 1967; Lee & Dubinsky, 2003). This result is also consistent with previous literature, which found that people are more willing to interact and form positive relationships with physically attractive people as they are perceived to be more social and more trustworthy (Ahearne et al., 1999). Additionally, streamer interaction orientation was found to have positive influences on swift guanxi. It has been consistently reported that interaction orientation positively affects relationship formation. This result is also consistent with previous literature, which found that the vendor interaction-oriented communication style reflects greater capability and credibility (Wu et al., 2017), helps friendship building, and fosters good customer relationships (Williams & Spiro, 1985). In addition, this supports previous studies that interaction-oriented salespeople actively interact with consumers and provide them with assistance, leading to increased customer satisfaction, comfort (Li & Ma, 2022; Roongruangsee et al., 2022), and willingness to engage (Yao et al., 2022).

Moreover, the study found that within the technical attributes, only the media richness of live streaming commerce platforms plays a crucial role in the formation of swift guanxi, while personalisation does not show a significant impact. The significant relationship between media richness and swift guanxi aligns with previous studies by Zhang et al. (2023) and Sheer (2011), emphasising the importance of media richness in relationship building, particularly in the current digital era where users are exposed to numerous live streaming commerce platforms. Vivid product presentations, combined with rich chat features, help foster mutual understanding between users and streamers, thereby facilitating relationship formation (Hsu et al., 2020; Tseng et al., 2017). Furthermore, as emphasised by Tseng et al. (2022), media richness also cultivates a warm feeling of connection with a human being among users, thus fostering offline-like relationships.

Surprisingly, personalisation contradicts previous predictions that it does not have a significant effect on swift guanxi despite some earlier studies finding a positive association between personalisation and relationship quality (Chen et al., 2022). This may be attributed to the two-sided nature of personalisation. While today's live streaming commerce users are more educated and sophisticated, seeking a more personalised service (Prasad et al., 2019), the significant privacy violations experienced by Chinese live streaming commerce users pose a threat to this demand. Accurate personalisation requires large amounts of personal data (Chen et al., 2022). The more precise the personalisation, the greater the amount of personal information required. The accuracy of personalised recommendations raise privacy concerns for users, and as a result, they may be unwilling to interact with streamers and form relationships with them.

Compared to other online selling (such as e-commerce and s-commerce), live streaming commerce provides more options for streamers to connect with users, allowing streamers and users to establish communication and relationships like offline interactions (Wongkitrungrueng et al., 2020). This study offers evidence of three streamer attributes and one technical attribute playing roles as social and technical factors, respectively, in the establishment of swift guanxi with users, thus supplementing the limited literature in this field. Therefore, streamer attributes and technical attributes are crucial in establishing connections with viewers, especially during sales in live streaming commerce.

Finally, in line with the assertion that swift guanxi plays a role in shaping consumer behaviour (Ou, Pavlou, & Davison, 2014), the present study suggests that swift guanxi is the strongest predictor of purchase intentions in live streaming commerce among millennials. Previous literature provides evidence that swift guanxi is particularly significant for Chinese shoppers, who place value on harmonious emotional factors when browsing products on online platforms (Lin et al., 2019; N. Luo et al., 2016). The study conducted by Chen et al. (2021) also demonstrated that mutual understanding, reciprocal, and harmonious swift relationships reduce consumer uncertainty and ensure smooth transactions. This implies that live streaming commerce companies should shift from traditional marketing approaches to a collaborative approach and actively cultivate informal swift guanxi with users.

6.2.3 Discussion on the Mediating Role of Swift Guanxi

Regarding the third objective, the results highlight the crucial role of swift guanxi in connecting streamer attributes and technical attributes with purchase intention, grounded in Mehrabian and Russell's S-O-R model. However, contrary to the initial hypothesis, the mediating effect of swift guanxi that links personalisation to purchase intention is insignificant. This difference can be attributed to the price attractiveness brought by personalised recommendations. Live streaming commerce platforms recommend similar products based on users' visit history to ease comparisons, which facilitates users in selecting the most cost-effective product from a wide range of similar products (CNNIC, 2023; Wang et al., 2023). This price attractiveness can enhance users' perceived value and satisfaction, lower their perception of risk (Chang & Wildt, 1994; Grewal et al., 1998; Piri & Lotfizadeh, 2015), and enable them to make purchases directly based on the platform's personalised recommendations without relying on swift guanxi.

In contrast, the mediating effect of swift guanxi that links social-technical attributes to purchase intention is significant for the remaining hypothesis among millennial shoppers. This conforms to the S-O-R model that environmental attributes (social and technology attributes) impact consumers' affective reactions (swift guanxi) and consequently their behavioural responses (i.e. purchase intention) (Fan et al., 2019; Mehrabian & Russell, 1974). It is worth noting that swift guanxi serves as a partial mediator in the relationship between expertise, interaction orientation, and purchase intention, indicating the potential for other mediating effects. This aligns with prior studies that perceived value (Guo et al., 2022) and perceived persuasiveness (Gao et al., 2021) fully mediate the relationship between streamers' expertise and purchase intention. Additionally, research has shown that parasocial relationship fully mediate the connection between interaction orientation and purchase intention (Liao et al., 2022).

Furthermore, swift guanxi fully mediates the relationship between attractiveness, media richness, and purchase intention. This can be interpreted as users being attracted to and interacting with appealing streamers, but that attraction does not guarantee purchases from them, as their attractiveness may not be relevant to the product being offered (Park & Lin, 2020; Sokolova & Kefi, 2022). Previous research also suggests that media richness only promotes purchases when users trust the source (Chen et al., 2016).

Swift guanxi between the customer and the streamer is thus requisite to facilitate purchase intention. The current finding is also consistent with that of Lin et al. (2017) and Shi et al. (2018), who reported the mediating effect of swift guanxi on repurchase intention. Owing to the growth of Chinese online marketing, swift guanxi is now a primary tool for retailers to establish harmonious relationships with their viewers (Ou, Pavlou, & Davison, 2014). On a similar note, Fan et al. (2019) identified that swift guanxi is a prerequisite for the success of social commerce. The swift guanxi that takes place on an online marketing platform evokes positive impacts on marketing performance, such as improving customer engagement, increasing sales, and retaining existing customers (Chen et al., 2021; Lin et al., 2019; Zhou et al., 2023).

Undoubtedly, customer relationship management (i.e., swift guanxi) is imperative in the context of Chinese live streaming commerce. Contemporary marketing should consider strategies to quickly create harmonious bonding (i.e., build and boost relationships with viewers) through guanxi. In this case, when streamer expertise, attractiveness, interaction orientation, and media richness are enhanced, swift guanxi is the key factor that contributes to purchase intention. That is, social and technical attributes are significant environmental attributes that trigger consumers to swiftly form guanxi with streamers, which eventually shapes their purchase behaviour. Swift guanxi is an emerging concept, both conceptually and empirically, that closely relates to the management of streamer-consumer relationships (Ou, Pavlou, & Davison, 2014). Essentially, this study provides clear evidence of the important role of swift guanxi in the live streaming commerce domain.

6.2.4 Discussion on the Moderating Role of PEEIM

The final research question focuses on examining how PEEIM exerts moderating effects on purchase intention. As predicted, the influence of swift guanxi on the purchase intention path is greater among users with high PEEIM. This suggests that vigilant Generation Y users have greater confidence in purchasing when they perceive higher PEEIM. This significant finding aligns with the conclusions of Chen et al.

(2022), indicating that PEEIM, through third-party mechanisms, reduces consumer uncertainty and leads to positive responses. Therefore, this study proves that live streaming commerce companies should enhance PEEIM for users, such as third-party assurance mechanisms, escrow services, and privacy protection.

6.3 Theoretical Contributions

The present study contributes to the body of knowledge in four different aspects. First, this study extends the use of socio-technical theory (Trist et al., 1963) to the context of live streaming commerce. Tracing its roots to information system theories, both social and technical factors are essential to the success of the system. Responding to Ma's (2021) suggestion, both streamer attributes (i.e., social factors) and technical attributes (i.e., technical factors) were integrated for an optimal live streaming commerce marketing strategy. In particular, the results of this study establish that streamer expertise, interaction orientation, and personalisation represent the environmental factors that should be incorporated in driving live streaming commerce intention. Conversely, streamer attractiveness and media richness only indirectly impact purchase intention through swift guanxi. Although previous literature has reported the benefits of streamer attraction and media richness, the findings of this study suggest that streamer attraction and media richness alone are not powerful enough to drive purchase intention, especially in content-based live streaming commerce platforms where high risk exists, thus adding value to existing knowledge. Attractive streamers can capture viewers' attention and create a favourable impression. However, this attraction does not directly translate into purchase intention. Streamers can leverage their attractiveness and other characteristics to capture users attention, actively interact with them, and form swift guanxi, which leads to purchase intention.

Therefore, it is critical to consider guanxi strategies in live streaming commerce to influence purchases through streamer attractiveness and media richness.

Second, this study contributes to the literature by identifying the antecedents and outcomes of swift guanxi in live streaming commerce. Using Mehrabian and Russell's (1974) S-O-R model, the study supports the relationship between digital attributes, swift guanxi, and purchase intention. Specifically, it suggests that streamers attributes (e.g., expertise, attractiveness, and interaction orientation) combined with technical attributes (e.g., media richness) can effectively drive swift guanxi. Most notably, the study reveals that swift guanxi is the strongest predictor of purchase intention in live streaming commerce among millennials. These findings highlight that swift guanxi is especially important to Chinese shoppers, who value harmonious emotional relationships when shopping online (Lin et al., 2019; Luo et al., 2016). Therefore, this study enhances our understanding of the new paradigm of swift guanxi by broadening the scope of its antecedents through an integrated social and technical perspective and exploring its critical role in influencing purchase intention within the live commerce.

Third, the present research contributes to the existing literature by unveiling the critical role of swift guanxi as a mediating mechanism in the live streaming commerce purchase intention. Mehrabian and Russell’s (1974) S-O-R model was employed to elucidate the connection between environmental factors of live streaming commerce and purchase intention. Specifically, this study reveals a mediation process in which environmental factors (e.g., streamer expertise, attractiveness, interaction orientation, and media richness) influence consumers’ purchase intention via swift guanxi. Notably, it demonstrates the urgent need for guanxi (i.e., swift guanxi) management in the Chinese online marketplace. These findings align with previous assertions that the low mechanism security of Chinese social commerce and Confucian culture lead Chinese users to rely more on guanxi for transactions (Fan et al., 2019; Lin et al., 2019; Ou, Pavlou, & Davison, 2014). A high level of swift guanxi in the Chinese online marketplace can result in positive responses, including purchase intention. Thus, this research complements prior studies that merely focused on direct links by providing a clear and comprehensive understanding of the mechanisms that enhance purchase intention. Consequently, the critical role of swift guanxi, especially in attracting millennial consumers, should be given greater attention in future studies on live streaming commerce.

Finally, this study provides new insights into the live streaming commerce literature by exploring the moderating role of PEEIM on the relationship between swift guanxi purchase intentions, drawing on the theoretical basis of URT (Berger & Calabrses, 1975). Previous research has emphasised the moderating role of PEEIM in the effectiveness of relationship quality (Fang et al., 2014; Huang et al., 2017). However, swift guanxi is different from relationship quality in Western contexts (e.g., trust or satisfaction) (Ou, Pavlou, & Davison, 2014). By empirically investigating the moderating effect of PEEIM in live streaming commerce, this study expands our understanding of constraint factors that may hinder the relationship between swift guanxi and purchase intention. Additionally, the application of URT in live streaming commerce literature for behavioural research has been limited. This study broadens the application of URT to the live streaming commerce context, providing theoretical alternatives to explain users' inconsistent decision-making. Moreover, the moderation results reveal that PEEIM positively moderate the relationship between swift guanxi and purchase intention. Overall, these empirical findings fill a gap in the existing literature and provide new insights into the role of PEEIM in the relationship between swift guanxi and purchase intention, especially in the context of live streaming commerce.

6.4 Practical Contributions

In addition to theoretical contributions to the literature, this research also provides significant managerial implications, particularly for retailers, information system managers, and the government.

6.4.1 Streamers

This study provides direction on the attributes that streamers should emphasise on to drive users' purchase intention. Although live streaming provides the possibility of interaction between streamer and users, the expertise of the streamers remains the most important social factor. Streamers can actively participate in training courses to improve their product knowledge and skills, enabling them to offer personalised recommendations to consumers. In addition, it is recommended that streamers create a small team of professionals to help them select high-quality products and prepare well-designed and informative content, as this can easily motivate consumers to make purchases based on compelling recommendations from experts.

In addition, attractiveness is another important characteristic of a streamer. Streamers can improve attractiveness by choosing the right makeup, adopting appealing hairstyles, wearing fashionable attire, and managing their weight (Ahearne et al., 1999). For example, studies has indicated that specific colours of clothing, such as red and black, are linked with higher judgments of attractiveness (Roberts et al., 2010).

Moreover, streamers can communicate with users in an interactive-orientated way and lead consumers to a positive emotional experience to capture the millennial market. These digital natives are more likely to value a streamer who maintains a connection with them in addition to offering professional information. Unlike personality, salespeople have the ability to manage their communication style (Williams & Spiro, 1985). Live streamers should enhance real-time interaction with viewers during live broadcasts, pay attention to immediate feedback on viewer actions (e.g., going into the live room, liking, following, retweeting, and making purchases), and utilise a variety of incentives to boost viewer engagement. For example, streamers could organise prize draws in live broadcasts. Additionally, they could ask viewers to provide feedback: "If you want to quickly buy the right product and learn more about it, please reply 1" or "If you want to chat and interact with me, please reply 2". Other initiatives include paying attention to viewers' online feedback in the bullet comment section and interacting with viewers.

Lastly, this research emphasises the mediating role of swift guanxi. Consequently, it is recommended for companies and streamers to concentrate on the three dimensions of swift guanxi (mutual understanding, reciprocal favours, and relationship harmony) to enhance swift guanxi. Streamers can achieve mutual understanding by attentively listening to ensure proper understanding of the buyer's comments and then responding in a timely and reasonable manner. In cases where buyers pose unclear questions, streamers should verify the meaning of these questions with the buyers. Furthermore, they can offer extra freebies or special pricing to encourage reciprocity. Steamers can also cultivate a harmonious relationship through reciprocity, such as by providing high-quality information and proactively addressing potential user disputes during purchases. By implementing these strategies, it is expected to promote swift guanxi between streamers and users.

6.4.2 Information Systems Management

This research provides practical insights into information systems management, particularly in the development and implementation of effective features to maximise media richness and personalisation. The empirical results of this study indicate that the higher the media richness, the more likely millennial shoppers are to form positive and swift guanxi with live streamers. This is an exciting signal for practitioners as media richness and personalisation of live streaming commerce are likely to yield returns in swift guanxi and purchase intention. Due to the rapid advancement of communication technology, there is a growing demand for enjoyable, interactive, attention-grabbing, and personalised technology, prompting live streaming commerce platforms to consider offering richer interactive media and personalised recommendations. These features can help establish better interpersonal relationships between live streamers and users and enhance user purchase intention.

Enhancing the media richness of live streaming commerce can be a key strategy to capture the attention of millennial shoppers (Chen & Chang, 2018). Therefore, application developers are advised to embed more vibrant features into live streaming commerce, such as using MR/VR technology to provide 360-degree full-view immersion. Additionally, other senses should be gradually simulated to offer a more immersive product display. These strategies are expected to facilitate a better understanding of products as well as between users and live streamers. Furthermore, developers of live streaming commerce platforms can introduce more emojis, voice dialogues, and other features to enhance interaction among users and improve interpersonal relationships between users and live streamers (Li et al., 2019; Tseng et al., 2022).

In addition, the personalisation strategy of live streaming commerce platforms is crucial for increasing the purchase intention of millennial shoppers. For example, artificial intelligence provides live streaming commerce platforms with the opportunity to showcase and provide personalised content to consumers based on their location, device, past interactions, demographics, and other information. These features send tailored information to meet individual needs, thereby stimulating purchase intent. Moreover, platform developers should focus on increasing the serendipity of personalised recommendations to avoid the "information cocoon" trap. In summary, integrating personalised recommendations and providing a more intelligent and efficient live streaming commerce experience for users is a clear trend.

Finally, live streaming commerce platforms should consider enhancing the platform's security mechanisms. High levels of PEEIM can reduce buyer uncertainty about transactions, facilitating a more effective reduction of perceived uncertainty in swift guanxi. For instance, platform managers should thoroughly consider the buyer's needs for transaction security before, during, and after purchase. Live streaming commerce platforms can also collaborate with third parties to enhance payment security, information security, and other safeguard mechanisms, creating a secure transaction environment for buyers.

6.4.3 Policymakers

Policymakers make up another key stakeholder influencing the development of the live streaming commerce industry. With the rise of live streaming commerce, most merchants need to invest more to support live streaming commerce. However, small and medium enterprises (SMEs) may face the challenge of limited resources and financial support. In this regard, the role of policies formulated by the government in supporting SMEs in the live streaming commerce industry is very important. First, the government can promote the establishment of an industry certification system to certify the level of professional skills of streamers through examinations. This will not only help enhance the professionalism of the streamers, but also provide more accurate reference for retailers. Second, financial support can be provided to SMEs through tax breaks or financial incentives. For example, a special innovation fund can be set up to support SMEs' innovative projects in the field of live streaming commerce and enhance their competitiveness. The government can also promote the co-development of the live streaming commerce industry with several related fields, such as digital technology, artificial intelligence, and virtual reality, through cooperation agreements to promote the growth of the digital economy. Finally, it is advisable for policymakers to establish a more efficient institutional framework for the entire social commerce environment and to effectively convey the risk-mitigation benefits of this infrastructure to the online public. Creating a visibly secure social commerce environment has the potential to ease purchase decisions for vendors in live streaming commerce, thereby playing a role in fostering the success of live streaming commerce in their respective regions. Overall, policymakers should take decisive and prudent measures to help live e-commerce marketing for SMEs become an important part of the digital economy, which contributes to the development of China's digital economy in many ways by creating jobs, boosting business activities, facilitating scientific and technological innovations, and improving digital content output, social interactions, and digital marketing.

6.5 Limitations and Future Research Directions

Despite these contributions, this study has some limitations that require further investigation in the future. First, the sample of this study was China's Gen-Y, thus restricting the generalisability of the findings to the whole population. Although Gen-Y accounts for a sizable portion of the e-commerce population, it is still necessary to examine the views of other populations, as different factors may be involved in the purchase intention, such as the consideration of internet self-efficiency for Gen-X (Chung et al., 2010) and product uniqueness for Gen-Z (Goldring & Azab, 2021).

Second, guanxi is a culture-specific concept in China, and the research is conducted in the context of the Chinese live streaming commerce. Considering different cultures, the results of this model may not be fully generalisable. To overcome this limitation, further research should examine the applicability of the research model in the contexts of other cultures. For example, research studies on "ubuntu" in Africa and "buen vivir" in Peru can broaden the understanding of relational concepts between buyers and sellers.

Finally, the insignificant relationship between media richness and purchase intention provides an interesting direction for future research. Despite ample evidence that media richness significantly increases purchase intention (e.g., Chen & Chang, 2018; Chen et al., 2016), the present study yielded a contradictory result. The reason for this insignificant result may be that the present study ignored some factors. As Li and Meshkova (2013) stated, rich media product displays are more effective for experiential goods. To consolidate existing knowledge, it would be interesting for future research to explore how product categories as moderators strengthen or weaken the relationship between media richness and live-streaming commerce purchase intention.

6.6 Conclusion

This study makes significant contributions to theoretical and managerial perspectives by proposing a model to understand the perceptions of millennial shoppers in their purchase decisions. First, this study offers a comprehensive insight into the determinants of live streaming commerce purchase intention. The results revealed that purchase intention is positively impacted by streamer expertise, interaction orientation, and personalisation but not by streamer attractiveness and media richness. This raises the notion that social attributes and technical attributes should be work together to improve users' purchase intention. Second, this study reveals the antecedents of swift guanxi (e.g., expertise, attractiveness, interaction orientation, and media richness) and highlights the role of swift guanxi in enhancing users' purchase intention in live streaming commerce. Third, the findings showed that swift guanxi is an important mechanism that should not be overlooked when taking into account the influences of streamer attributes (e.g., streamer expertise, attractiveness, and interaction orientation) and technical attributes (e.g., media richness) on purchase intention. This suggests that the relationship between streamers and consumers is essential in providing consumers with a more profound and exceptional experience when using live-streaming commerce. Lastly, consistent with previous literature, PEEIM was found to moderate the relationship between swift guanxi and purchase intention in the context of live streaming commerce. When users perceive high PEEIM, the relationship between swift guanxi and purchase intention tends to be higher. This phenomenon fits the characteristics of millennials, as they are generally sceptical and emphasise emotional connection when interacting with retailers on online platforms. Apart from that, this chapter addressed the limitations of this study and made suggestions for future research in this field. Overall, this study has reinforced the understanding of the determinants that impact live streaming commerce purchase intention among millennial shoppers in China.

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APPENDICES

Appendix 1

Questionnaire Sample

Respondent No:

Invitation to Participate in a Survey on:

Factors Influencing Millennial Consumers' Purchase intention in the Context of Live Streaming Commerce in China

Dear Sir/Madam,

I am a Ph.D. student from Universiti Putra Malaysia (UPM). This research is part of my Ph.D dissertation entitled "*Factors Influencing **Millennial** Chinese Consumers' Purchase intention in the Context of Live Streaming Commerce*". This is an academic exercise to gain the much insight on factors that influence consumers' purchase intention towards live streaming commerce in China. This research is to offer findings and recommendations to assist the relevant stakeholders.

I would be grateful if you could spend 10 -15 minutes to complete this survey. There are no right or wrong answers and your responses to all the questions/statements should be entirely based on your own views and experience. Please be assured that all the information you provide will be kept confidential. Completion of the survey shall be taken as proof of consent to participate in this study.

For any inquiry, please contact me at email: yingxlee@foxmail.com

Your participation and support are very much appreciated. Thank you very much for your time.

Regards,
Li Yingxia(GS60229)
Ph.D. candidate
School of Graduate Studies,
Universiti Putra Malaysia

Screening Questions

Screening questions were placed at the beginning of the survey.

Instructions: This section aims to find out if you meet the criteria for this survey. Please check (√) the box that best represents your opinion.

1. Are you from mainland China? (Please tick "√" one box only)

   ☐ Yes ☐ No

2. Are you born between 1981 and 1996? (Please tick "√" one box only)

   ☐ Yes ☐ No

3. In the last three months, do you have live streaming shopping experience on any of the three platforms (Douyin, Kuaishou, Xiaohongshu)?

   ☐ Yes ☐ No

Participants who answered "yes" to all these screening questions were asked to fill in the remainder of the survey. Unqualified participants were denied further access.

SECTION A:

Live Streaming Commerce Usage

Instructions: This section intends to capture the details about your live streaming commerce usage. Please tick (√) in the box that most represents your opinion.

1. Which of the following is your PREFERRED live streaming commerce platform? (Please tick "√" one box only)

☐ Douyin ☐ Kuaishou ☐ Xiaohongshu

2. How long have you been using live streaming shopping? (Please tick "√" one box only)

☐ 3-6 months. ☐ 7-12 months

☐ 13-18 months ☐ 19-24 months

☐ 25-30 months ☐ 31 months and above

3. How often do you make purchases on Live Commerce? (Please tick "√" one box only)

☐ Daily ☐ Weekly ☐ Monthly

☐ Once every 2-3 months ☐ Once every 4-6 months ☐ Once a year or less

4. Which of the following is the product that you most frequently purchase via live streaming shopping (You may tick "√" **more than one** box)

☐ Apparel ☐ Daily Household

☐ Cosmetics ☐ Food & Health

☐ Sports & Travel ☐ Books & Audio

☐ Electronic ☐ Jewelry

☐ Maternal & Child

SECTION B:

Perception Towards Live Streaming Commerce

Instructions: This section focuses on your perception of our PREFERRED live streaming commerce platform (see your response in Q1, Section A). Please read each statement below and indicate your response by circling the appropriate number (on a 5-point scale given below) which best describes you. Please be reminded that there are no right or wrong answers.

1	2	3	4	5
Strongly Disagree	**Disagree**	**Neutral**	**Agree**	**Strongly Agree**

Streamers Attributes					
Expertise	**Strongly Disagree**	**Disagree**	**Neutral**	**Agree**	**Strongly Agree**
The live streamers are expert in products.	1	2	3	4	5
The live streamers have experience in products.	1	2	3	4	5
The live streamers are very knowledgeable about products.	1	2	3	4	5
The live streamers provide substantial information regarding products.	1	2	3	4	5
Attractiveness	**Strongly Disagree**	**Disagree**	**Neutral**	**Agree**	**Strongly Agree**
The live streamers are quite handsome/pretty.	1	2	3	4	5
The live streamers are attractive physically.	1	2	3	4	5
I feel the live streamer is very good looking.	1	2	3	4	5
Interaction orientation	**Strongly Disagree**	**Disagree**	**Neutral**	**Agree**	**Strongly Agree**
The live streamers genuinely enjoy helping audiences.	1	2	3	4	5
The live streamers are easy to talk with.	1	2	3	4	5
The live streamers like to help audiences.	1	2	3	4	5
The live streamers are a cooperative person.	1	2	3	4	5
The live streamers try to establish a personal relationship.	1	2	3	4	5
The live streamers seem interested in me not only as a customer, but also as a person.	1	2	3	4	5
The live streamers are friendly.	1	2	3	4	5

Technical Attributes					
Media Richness	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
The live-stream channel allows me to give and receive timely feedback.	1	2	3	4	5
The live-stream channel helps me communicate quickly.	1	2	3	4	5
The live-stream channel allows users to communicate with different types of messages, such as audio, video, text, and stickers.	1	2	3	4	5
The live-stream channel helps me better understand others and satisfy each other's needs.	1	2	3	4	5
Personalization	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
The live-stream channel understands my personalized needs.	1	2	3	4	5
The live-stream channel offers me targeted recommendations based on my preferences.	1	2	3	4	5
The live-stream channel meets my personalized needs basically.	1	2	3	4	5

Swift Guanxi					
Mutual understanding	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
The live streamers and I understand each other's needs.	1	2	3	4	5
The live streamers and I understand each other's point of view.	1	2	3	4	5
The live streamers and I can make ourselves heard.	1	2	3	4	5
The live streamers and I can follow the flow of conversation	1	2	3	4	5
The live streamers and I show interest in each other's opinions	1	2	3	4	5
Reciprocal favors	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
If I buy from the live streamer, he/she will provide a discount for me.	1	2	3	4	5
The live streamers and I offer positive ratings or comments to each other.	1	2	3	4	5
The live streamers and I help each other.	1	2	3	4	5
The live streamers and I proved to be friends by doing favors for each other.	1	2	3	4	5
Relationship harmony					
The live streamers and I maintain harmony.	1	2	3	4	5
The live streamers and I avoid conflict.	1	2	3	4	5

The live streamers and I respect each other.	1	2	3	4	5
Overall, I quickly formed an interpersonal guanxi with streamer.	1	2	3	4	5

PEEIM					
	Strongly Disagree	**Disagree**	**Neutral**	**Agree**	**Strongly Agree**
When buying on this platform, I am confident that there are mechanisms in place to protect me against any potential risks (e.g. leaking of personal information, credit card fraud, goods not received, etc.) of online shopping if something goes wrong with my online purchase.	1	2	3	4	5
I believe that there are other parties (e.g. my credit card company) who have an obligation to protect me against any potential risks (leaking of personal information, credit card fraud, goods not received, etc.) of online shopping if something goes wrong with my online purchase.	1	2	3	4	5
I am sure that I cannot be taken advantage of (e.g. leaking of personal information, credit card fraud, goods not received, etc.) as a result of conducting purchases on this platform.	1	2	3	4	5

Purchase Intention					
	Strongly Disagree	**Disagree**	**Neutral**	**Agree**	**Strongly Agree**
Given the chance, I predict that I would consider purchasing products from streamers on this platform in the future.	1	2	3	4	5
It is likely that I will actually purchase products from streamers on this platform.	1	2	3	4	5
Given the opportunity, I intend to purchase products from streamers on this platform.	1	2	3	4	5

SECTION C:

Instructions: This section intends to capture your demographic profile. Please tick (√) for your responses. Your response will remain anonymous.

1. **Gender**

☐ Male ☐ Female

2. **Age**

☐ 27-30 years old ☐ 31-35 years old
☐ 36-42 years old

3. **Highest level of education**

☐ Second school or below ☐ Junior college
☐ Undergraduate Degree ☐ Graduate Degree
☐ Postgraduate Degree or higher

4. **Occupation**

☐ Employee- Government sector ☐ Employee - Private sector
☐ Self-employed ☐ Student
☐ Others, please state:

5. **Monthly Income**

☐ Less than RMB 3,000 ☐ RMB 3,001-RMB 5,000
☐ RMB 5,001-RMB7,000 ☐ RMB 7,001-RMB9,000
☐ RMB 9,001-RMB11,000 ☐ RMB 11,001-RMB13,000
☐ RMB 13,001-RMB15,000 ☐ More than RMB 15,000

END OF SURVEY

THANK YOU FOR YOUR PARTICIPATION!

Appendix 2

Ethic Committee Approval

UPM
UNIVERSITI PUTRA MALAYSIA
BERILMU BERBAKTI

PEJABAT TIMBALAN NAIB CANSELOR (PENYELIDIKAN DAN INOVASI)

OFFICE OF THE DEPUTY VICE CHANCELLOR (RESEARCH AND INNOVATION

Rujukan kami : UPM.TNCPI.800-2/1/7

Tarikh : 29 November 2023

Dr. Norazlyn Kamal Basha
Department of Management and Marketing
School of Business and Economics
Universiti Putra Malaysia
Serdang, Selangor

Dear Madam/Sir,

RESEARCH PROJECT: FACTORS INFLUENCING CHINESE CONSUMERS' PURCHASE INTENTION IN THE CONTEXT OF LIVE STREAMING COMMERCE

REFERENCE NO: JKEUPM-2023-1207

PRINCIPAL INVESTIGATOR: DR. NORAZLYN KAMAL BASHA

CO-INVESTIGATOR: ASSOC. PROF DR. SERENE NG SIEW IMM, LI YINGXIA (STUDENT)

The Ethics Committee for Research involving Human Subjects of University Putra Malaysia (JKEUPM) has studied the proposal for the above project and found that there were no objectionable ethical issues involved in the proposed study.

Please find the list of documents received and reviewed with reference to the study and committee members who reviewed the documents (as attached).

Notwithstanding above, we will not be responsible for any misconduct on the part of researcher in the course of carrying out the research.

Ethical approval is required in the case of amendments/ changes to the study documents/ study sites/ study team.

Thank you.

"WITH KNOWLEDGE WE SERVE"

Sincerely yours,

PROF. DR. NORMALA IBRAHIM
Chair
Ethics Committee for Research involving Human Subjects
Universiti Putra Malaysia

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ETHICS COMMITTEE FOR RESEARCH INVOLVING HUMAN SUBJECTS
(JKEUPM)
UNIVERSITI PUTRA MALAYSIA

Research title	:	**Factors Influencing Chinese Consumers' Purchase intention in the Context of Live Streaming Commerce**
Study Site	:	**China**
JKEUPM Ref No.	:	**JKEUPM-2023-1207**
Principal Investigator	:	**Dr. Norazlyn Kamal Basha**
Co-investigator	:	**Assoc. Prof Dr. Serene Ng Siew Imm, Li Yingxia (Student)**

Documents received and reviewed with reference to the above study:

1. Ethics Application Form, Version 1 dated 15/09/2023
2. Respondent's Information Sheet / Consent (English), Version 2 dated 25/09/2023
3. Respondent's Information Sheet / Consent (Chinese), Version 2 dated 25/09/2023
4. Proposal (English), Version 2 dated 27/11/2023
5. Questionnaires/Interviews (English), Version 1 dated 15/09/2023
6. Curriculum Vitae of:
   a. Dr. Norazlyn Kamal Basha
   b. Assoc. Prof Dr. Serene Ng Siew Imm
   c. Li Yingxia

The University Research Ethics Committee, Universiti Putra Malaysia (JKEUPM) operates in accordance to the ICH-GCP Guidelines.
Decision by JKEUPM:

[x] Approved

[x] **Permission MUST BE OBTAINED from the respective hospitals/ institutions before conducting the research**

[ ] Disapproved

Please note that the approval is **VALID UNTIL 29 NOVEMBER 2024**

Researchers should comply with the following:

I. Complete a Study Final Report upon study completion (Form 3.2).

II. Ethical approval is required in the case of amendments/ changes to the study documents/ study sites/ study team.

III. Applicable for Clinical Trial Studies and Clinical interventional Studies only: Progress Report has to be submitted to JKEUPM at every 6 months from the date of approval (Form 3.1). Report occurrences of all Serious Adverse Events (SAEs), Suspected Unexpected Serious Adverse Reaction (SUSARs) and Protocol Deviation/ Violation at all JKEUPM approved sites to

JKEUPM. All serious adverse events (SAEs) detected or being notified should be reported immediately to the sponsor except for those SAEs that the protocol or other document (e.g., Investigator's Brochure) identifies as not needing immediate reporting. The immediate reports should be followed promptly by detailed, written reports.

The required forms can be obtained from the Ethics Committee for Research Involving Human Subjects (JKEUPM) website (http://www.tncpi.upm.edu.my/faildokumen).

Date of Approval: 29 November 2023

Members of the JKEUPM who reviewed the documents:

i. Primary Reviewer: LAr. Ts. Dr. Adam Aruldewan S.Muthuveeran/Assoc. Prof Dr. Rosliza Abdul Manaf
ii. Information Consent Reviewer: Dr. Zalina binti Abu Zaid

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PROF. DR. NORMALA IBRAHIM
Chair
Ethics Committee for Research involving Human Subjects
Universiti Putra Malaysia

JKEUPM is recognised by The Strategic Initiative for Developing Capacity in Ethical Review (SIDCER) in collaboration with the Forum for Ethical Review Committees in Asia and the Western Pacific Region (FERCAP) for its compliance with the Declaration of Helsinki, International Conference on Harmonization (ICH) Guidelines, Good Clinical Practice (GCP) Standards, Council for International Organizations of Medical Sciences (CIOMS) Guidelines, World Health Organization (WHO) Standards and Operational Guidance for Ethics Review of Health-Related Research and Surveying and Evaluating Ethical Review Practices, EC/IRB Standard Operating Procedures (SOPs), and Local Regulations and Standards in Ethical Review.

BIODATA OF STUDENT

Li Yingxia received her Bachelor of Science degree from Henan University, China, in 2007. In 2011, she earned his Master of Science degree from Sun Yat-sen University in China. She is currently pursuing the Doctor of Philosophy in Marketing programme. Her areas of research interest are consumer behaviour, e-commerce, social media marketing, and quantitative research.

LIST OF PUBLICATIONS

Li, Y., Kamal Basha, N., Ng, S.I. and Lin, Q. (2024), "What makes viewers loyal toward streamers? A relationship building perspective and the gender difference", Asia Pacific Journal of Marketing and Logistics. (SSCI IF:3.9 JCR Q2 in Bussiness)

Li, Y., Kamal Basha, N., Ng, S.I. and Lin, Q. (2023), "Watch Now, Buy Now? Impact of Interpersonal Interaction Factors on Swift Guanxi and Purchase Intention in Live Streaming Commerce." Journal of Marketing Advances and Practices. (MyJurnal)

Lin, Q.L., Ng, S. I., Kamal Basha, N., Luo, X., & Li, Y. (2024). Impact of virtual influencers on customer engagement of Generation Z consumers: a presence perspective. Young Consumers. (ESCI)

Lin, Q. L., Ng, S. I., Basha, N. K., & Li, Y. X. (2024). Content Matters! The Effects of TikTok (Douyin) Short Video Content on Flow Experience, Trust, and Purchase Intention from the Signaling Theory Perspective. Journal of Marketing Advances and Practices. (MyJurnal)