INFLUENCING FACTORS OF NEW RETAIL USAGE BEHAVIOR OF GEN Y AND BABY BOOMERS IN CHINA: A COMPARATIVE STUDY BASED ON THE INTEGRATION OF UTAUT, HBM AND TORAOA WITH MEDIATING EFFECTS

GUO FUGANG

DOCTOR OF PHILOSOPHY
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GUO FUGANG (903356)

A thesis submitted to the Ghazalie Shafie Graduate School of Government in fulfilment of the requirement for the Doctor of Philosophy Universiti Utara Malaysia

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(College of Law, Government and International Studies)
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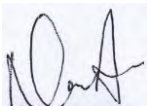
Penyelia Kedua (*Second Supervisor*)		**DR. NOOR AZURA AZMAN**	Tandatangan *(Signature)*	

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ABSTRACT

As the pandemic's impact diminishes, it becomes a new question whether people are eager to return to the pre-pandemic forms of retail services. This study adopts a combination of the Health Belief Model (HBM), Theory of Resistance Among Older Adults (TORAOA), and the Unified Theory of Acceptance and Use of Technology (UTAUT), aiming to explore from both promoting and inhibiting perspectives whether Gen Y and Baby Boomers still adhere to using new retail and which functionalities they utilise. This aspect has been overlooked in the past, especially as in the post-pandemic period. This study was conducted in Shanghai, a city with a relatively high level of economic development in China, and there were 399 valid questionnaires. SmartPLS was used to compare multiple groups' paths. The study found Generation Y and Baby Boomers are more likely to use self-service checkout systems and instant retail, and they frequently engage in this behaviour. Both groups disliked the e-commerce assistant's AI responses. The study found that perceived susceptibility, perceived severity, and perceived health benefits do not influence the perceived usefulness of new retail among Baby Boomers and Gen Y. This significant finding suggests that the pandemic is fading away from people's lives and no longer affects changes in their behaviour and thinking. The results showed that for Generation Y, perceived financial cost significantly affected their barrier cognition, which in turn had a negative impact on their intention to use. For the Baby Boomer group, multidimensional resistance factors such as digital device accessibility, privacy risks, self-efficacy, and action restrictions significantly increased their perceived barriers, further affecting their perception of technology usefulness and usage behaviour. In addition, perceived usefulness showed a significant mediating effect between barrier perception and behavioural intention in the Baby Boomer group, but this path did not hold true in the young group. This study supports retail service organisations in developing strategies aligned with the senior market. The study complements research on retail behaviour after COVID-19 disappears, especially in comparing Baby Boomers and Gen Y.

Keywords: Perceived barriers, Perceived health benefits, New retail, Movement restrictions

ABSTRAK

Apabila kesan pandemik semakin berkurangan, ia menjadi persoalan baharu sama ada orang ramai tidak sabar-sabar untuk kembali kepada bentuk perkhidmatan runcit pra-pandemi. Kajian ini mengguna pakai gabungan Model Kepercayaan Kesihatan (HBM), Teori Penentangan Dalam Kalangan Orang Tua (TORAOA), dan Teori Penerimaan dan Penggunaan Teknologi Bersepadu (UTAUT), yang bertujuan untuk meneroka dari kedua-dua perspektif menggalakkan dan menghalang sama ada Gen Y dan Baby Boomers masih mematuhi penggunaan runcit baharu dan fungsi yang mereka gunakan. Aspek ini telah diabaikan pada masa lalu, terutamanya dalam tempoh selepas pandemik. Kajian ini dijalankan di Shanghai, sebuah bandar yang mempunyai tahap pembangunan ekonomi yang agak tinggi di China, dan terdapat 399 soal selidik yang sah. SmartPLS digunakan untuk membandingkan laluan berbilang kumpulan. Kajian mendapati Generasi Y dan Baby Boomers lebih cenderung menggunakan sistem pembayaran layan diri dan runcit segera, dan mereka kerap terlibat dalam kelakuan ini. Kedua-dua kumpulan tidak menyukai respons AI pembantu e-dagang. Kajian itu mendapati bahawa persepsi kerentanan, persepsi keterukan dan manfaat kesihatan yang dirasakan tidak mempengaruhi persepsi kegunaan runcit baharu dalam kalangan Baby Boomer dan Gen Y. Penemuan penting ini menunjukkan bahawa wabak itu semakin hilang daripada kehidupan orang ramai dan tidak lagi menjejaskan perubahan dalam tingkah laku dan pemikiran mereka. Keputusan menunjukkan bahawa bagi Generasi Y, persepsi kos kewangan memberi kesan ketara kepada kognisi halangan mereka, yang seterusnya memberi kesan negatif ke atas niat mereka untuk menggunakan. Bagi kumpulan Baby Boomer, faktor rintangan pelbagai dimensi seperti kebolehcapaian peranti digital, risiko privasi, keberkesanan kendiri dan sekatan tindakan meningkatkan persepsi mereka dengan ketara, seterusnya menjejaskan persepsi mereka tentang kegunaan teknologi dan gelagat penggunaan. Di samping itu, kebergunaan yang dirasakan menunjukkan kesan pengantara yang ketara antara persepsi halangan dan niat tingkah laku dalam kumpulan Baby Boomer, tetapi laluan ini tidak berlaku dalam kumpulan muda. Kajian ini menyokong organisasi perkhidmatan runcit dalam membangunkan strategi yang sejajar dengan pasaran kanan. Kajian itu melengkapkan penyelidikan mengenai tingkah laku runcit selepas COVID-19 hilang, terutamanya dalam membandingkan Baby Boomers dan Gen Y.

Keywords: Perceived barriers, Perceived health benefits, New retail, Movement restrictions

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PSU	Perceived Susceptibility
PSE	Perceived Severity
PHB	Perceived Health Benefits
DE	Digital Equipment
PFC	Perceived Financial Cost
PR	Privacy Risk
PS	Perceived Self-efficacy
PB	Perceived Barriers
PU	Perceived Usefulness
SI	Social Influence
MR	Movement Restrictions
FC	Facilitating Conditions
EXP	Experience
ITU	Intention to Use
UB	Using Behaviour
HBM	The Health Belief Model
UTAUT	The Unified Theory of Acceptance and Use of Technology
TORAOA	Theory of Resistance Among Older Adults

CHAPTER ONE

INTRODUCTION

1.1 Background of Study

The pandemic has come and gone, leaving significant and lasting effects on consumer behaviour (Khayru, 2021; Ivkovic, 2021; Andrabi et al., 2024). Since the 1918 influenza pandemic, COVID-19 has become the most severe global pandemic of the past century (Ning et al., 2020). With 188,655,968 confirmed cases worldwide, the pandemic has resulted in a mortality rate of approximately 2.16 per cent, or 4,067,517 deaths (World Health Organisation, 2023). Lockdowns of varying durations have been enforced globally to curb the spread of the virus. This is a human tragedy, and that must be recognised. Besides greatly impacting public health, this pandemic has created challenges for global economic behaviour (Maital & Barzani, 2020). It has changed people's behaviour and daily routines, including how they travel, stay safe, and shop (Zhong et al., 2020; Vázquez-Martínez et al., 2021; El-Said & Aziz, 2022). People have adopted preventative measures to protect their health, such as avoiding close physical contact, washing their hands frequently, and steering clear of crowds (Jang et al., 2019; Everett et al., 2020). The pandemic has particularly affected various industries during the height of the outbreak, including retail, travel, healthcare, and other service sectors, causing notable disruptions and financial losses for many businesses (Nambiar, 2023).

Like many nations and regions, such as Malaysia and China, the pandemic's devastating impacts are gradually diminishing (Huang, 2023). This development is encouraging but raises new, important topics for research. For instance, the long-term effects of the pandemic have caused fundamental changes in people's behaviour and habits, such as online shopping, e-payments, and self-service, which persist even as the situation improves. Although the pandemic has ended, people still retain some of the habits they developed during it. Due to the pandemic, the use of mobile payment systems has increased significantly in Malaysia, signalling a shift from the pre-pandemic situation (de Best, 2023). In 2023, platforms such as GrabPay and Touch 'n Go had 23.3 million and 21.8 million users, respectively (Statista, 2023). Similarly, there have been notable changes in tourist behaviour in China, with individuals preferring to visit areas with lower population density and better ventilation, rather than venues like museums that may pose potential safety risks (Fan et al., 2023). These shifts in behaviour and preferences reflect the pandemic's lasting impact on societal norms and consumer choices, particularly in light of public health, the global economy, people's lives, and daily shopping (Li et al., 2020; Sayyida et al., 2021; Delasay et al., 2022).

1.1.1 Retail Industry

Retail refers to the commercial activity of directly supplying goods or services to consumers. According to The Free Dictionary (2023), retail involves directly providing products and services to end consumers, while offering products and services to other businesses is classified as non-retail. In some countries, retail is defined as transactions where 80% or more of the value occurs between businesses and end consumers, rather than between businesses and various levels of distributors (Pride

et al., 2018). This means the retail industry mainly serves individual consumers rather than other business entities.

The retail industry is experiencing steady growth and increasing global adoption of artificial intelligence technologies. According to Sabanoglu's (2023) data on Statista, the global retail market reached sales of $27 trillion in 2022 and is projected to reach $30 trillion in 2023. The retail sector is extensive worldwide, with the United States, China, and India being the largest markets, each surpassing $1 trillion in sales.

Notably, China reached $14.81 trillion in retail sales in 2022. Beyond its growth in scale, the global retail industry is also experiencing significant changes with the widespread adoption of artificial intelligence. Artificial intelligence plays a crucial role in online and offline omnichannel retail models, offering retailers smarter solutions to improve shopping experiences and operational efficiency (Sabanoglu, 2023).

The retail industry plays a crucial role in China's ongoing economic growth. Retail revenue in China from 2009 to 2019 has seen rapid expansion. In 2019, revenues reached 13.04 trillion yuan, showing an annual rise of 4.32% (Ma, 2020) (Figure 1.1). The National Bureau of Statistics reported that online retail sales in China from January to September 2018 amounted to 6278.5 billion yuan. In the new retail industry model, China's online retail sales of physical goods (4793.8 billion yuan) made up 17.5% of the total (27,429.9 billion yuan) (Wang, 2019). Therefore, the growth of the retail industry is vital for strengthening the country's economy.

Figure 1.1 Retail Revenue in China (2009-2019) by Ma (2020)

In 2020, the demand for contactless social media prompted a swift shift of the retail industry to digital retail. This indicates that the retail sector is undergoing transformation.

1.1.2 New Retail Industry

Digital consumption methods continue to expand rapidly in China. Despite the convenience and safety of instant retail, physical experience and customer service remain essential elements of the retail industry. The concept of new retail is merging online and offline sales channels to meet consumer demand (Cai & Lo, 2020). Furthermore, the new retail approach improves supply chain efficiency by utilising large databases and advanced technological systems. Li (2020) argues that technological transformation related to the digital economy will continue, and new retail concepts will shape the entire sales sector. Several previous studies have examined new retail concepts related to logistics strategy (Waker et al., 2018), future

retail trends (Li, 2020), and artificial intelligence technology (Wang, 2020). As digital technology keeps evolving, the scope of digital innovations in the retail industry extends well beyond what is commonly recognised.

Taking some standard technologies as examples, retail technology includes an AI-driven warehousing management system that uses virtual reality and artificial intelligence for automated spatial allocation, as well as replacing manual cargo handling with robotics (Yang et al., 2020). It also involves online services that enable interactive voice communication through AI agents and text-based interactions (Nica et al., 2022). Omni-channel retailing offers a variety of intelligent services in physical stores, such as self-service features for product localisation, price inquiries, autonomous checkouts, facial recognition-based payments, and mobile payment options (Fernandes & Pedroso, 2017; Liang et al., 2022).

Nowadays, the use of these technologies is no longer limited to the younger generation. China's ageing population has made the elderly an important demographic for technology adoption. Because of this group's considerable size, they can greatly influence the direction of China's retail industry.

1.1.3 Elderly Group

The elderly population is increasing rapidly and has become a major force in the consumer market. Advances in science and technology have led to many breakthroughs in the medical field, improving the human happiness index and accelerating the ageing process (Li et al., 2018). In 2019, individuals aged 65 and over accounted for 9% of the global population, with projections to rise to 16% by 2050

(United Nations, 2020). According to the UN, one of the most notable societal changes of the twenty-first century is ageing (United Nations, 2020).

Impacted by it, financial markets, transportation, housing, social security, commodity functions, commodity categories, services, family structures, and other social sectors have experienced notable changes and fluctuations; a new supply-demand relationship has emerged (United Nations, 2020). In the past, older adults were viewed as linked to poverty, illness, and frugality (Pal & Palacios, 2011; Rissanen & Ylinen, 2014; Jacques et al., 2021), but this perspective has gradually shifted. Society is increasingly seeing the elderly as representing wealth, activity, health, and consumption (Cui, 2025). Nowadays, local and multinational trading firms are adjusting their product and service strategies to cater to the elderly market (Failla, 2024; Xu, 2025). The Longevity Economy report released by the American Association of Retired Persons (2016) confirmed the growth of the elderly's spending power ($7.6 trillion in Economic Activity).

China is home to the world's largest elderly population, making it a region that warrants greater attention. According to data from the World Health Organisation (2023), China's elderly population had already reached 254 million by 2019. Soon (2023) argues that their product and service strategies to cater to the Chinese elderly market is important. Therefore, research focused on the elderly in China aligns with both economic development needs and ethical considerations.

1.1.4 Technology use by elderly people

Compared to other age groups, encouraging new retail among the elderly encounters greater difficulties. In the United Kingdom, Gen Z and Millennials lead in digital

behaviour, accounting for more than half of users. However, the adoption rate among those over 65 remains relatively low, at only 6% (U.K. Finance, 2019).

Fewer technology products are adopted by older adults with lower levels of digital literacy (Rasi et al., 2021). Low digital literacy levels have raised concerns among older adults regarding their ability to use mobile payments, prompting questions about the security of mobile payment systems within this group.

Furthermore, human memory, reasoning, sequencing, processing speed, and coordination decline with age after reaching adulthood (Salthouse, 2010). This indicates that seemingly simple technological tasks are not necessarily easy for them. Verbal and visual divergent thinking peak in adolescence and decline in older adulthood (Palmiero et al., 2017). Changes in the physical functioning of the elderly further hinder their ability to use technology.

Berge, a vice president at Mastercard in Stockholm, states that seniors are the largest untapped demographic for digital technology (Hares, 2020). In 2019, Berge launched the Betelningshj älpen campaign in Sweden, aiming to understand the digital behaviour of the elderly through training across 17 cities (Hares, 2020). All evidence suggests that technology adoption among the elderly remains an unresolved issue, covering various technologies within the retail industry. Indeed, pinpointing specific regional consumer tech behaviours requires more data.

1.1.5 Chinese Elderly People in Retail

In China, which has the world's largest elderly population, older consumers are moving from boycotting digital technology to embracing it. This shift could help remove

barriers to promoting technology use among the elderly. A significant event highlights the huge size of China's ageing population. The average life expectancy in China has risen from 33.28 years in 1950 to 78.59 years in 2022 (Statista, 2025), and over 297 million people are over 60 years old (Xinhua, 2024).

According to data provided by Statista (2023), as of 2021, the proportion of people over 60 in China had reached 18.94%, and this trend is expected to continue rising (Figure 1.2). Shopping is an everyday activity that is not significantly affected by age, especially when buying daily necessities. The growth of the elderly population presents a new challenge for the retail industry: how to best cater to them, particularly those aged 60 or older.

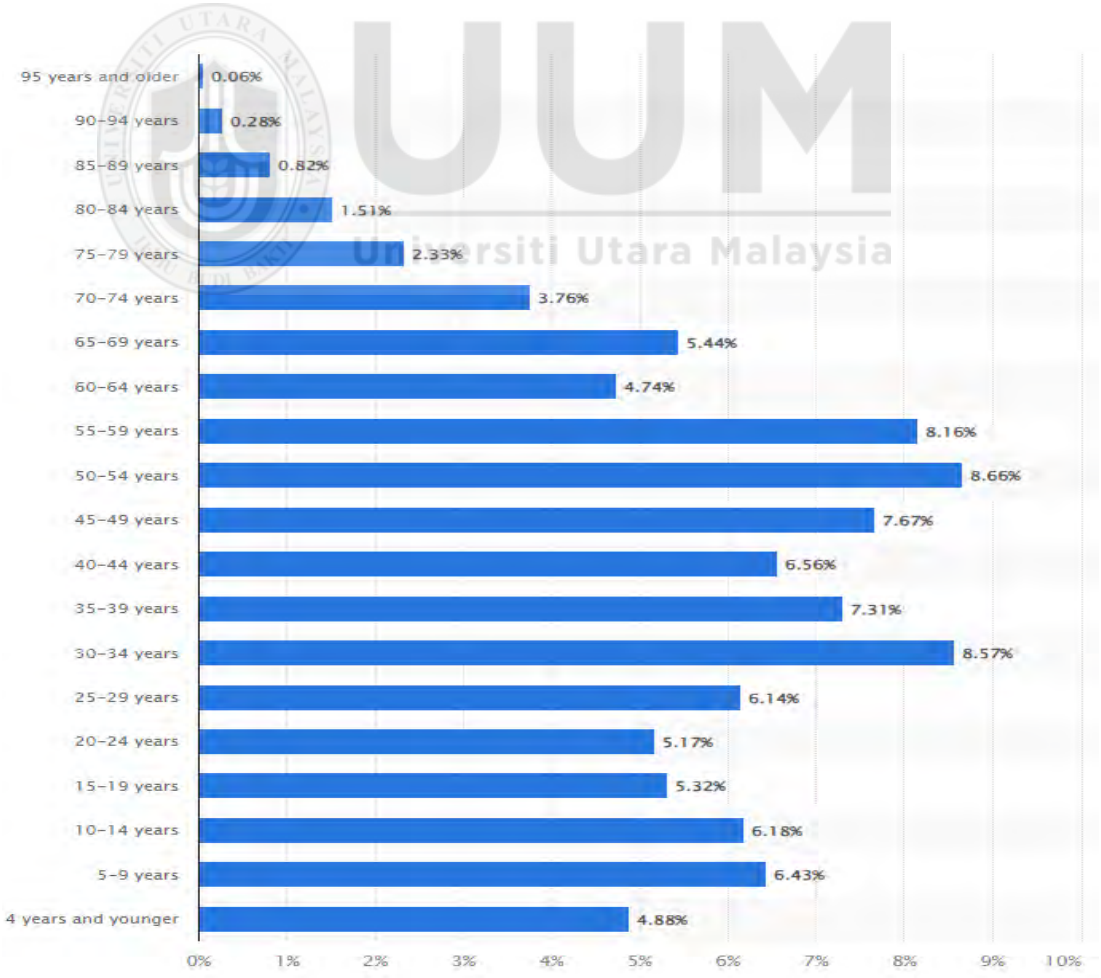


Figure 1.2 Population distribution in China in 2021 by Statista (2023)

Therefore, recognising the difference between the elderly and other consumer groups in China is vital for evaluating the current and future Chinese market. In China, online communication, instant retail, online shopping, online dating, online news, online video, online finance, online travel services, and online medical services have been adapted into user-friendly versions for the elderly (Stdaily, 2021). Such products have become essential products to improve life's enjoyment and have spread quickly among older adults (Stdaily, 2021). The transition of Chinese elderly individuals from non-digital natives to digital users has introduced new uncertainties regarding the adoption of digital technologies in retail services.

Today, elderly shoppers are often the main customers in supermarkets, enjoying more leisure time and having fewer family responsibilities. Outside of weekends, 60% or 70% of supermarket customers are senior citizens. In the fresh produce section, this figure rises to as much as 88% (Thepaper, 2021). Therefore, examining the retail sector offers a useful way to observe the elderly.

1.2 Problem Statement

Previous studies have not fully clarified how generational differences shape the ongoing adoption of new retail technologies in the post-epidemic period. Specifically, it remains unclear how factors based on the Unified Theory of Acceptance and Use of Technology (UTAUT), the Health Belief Model (HBM), and the Theory of Resistance of the Elderly (TORAOA) differently influence Generation Y and Baby Boomers. Additionally, there is still a gap in understanding the mediating variables that affect these behaviours (perceived usefulness). In this context, this study highlights the

importance of exploring this issue from various perspectives, including industry segmentation, practical issues, post-epidemic challenges, demographic concerns, location selection problems, variable-related practical issues, and research gaps.

1.2.1 Industry Segmentation Practical Problems

1.2.1.1 Instant Retail Market

The Chinese instant retail market has seen a gradual increase in the proportion of elderly consumers during the pandemic. However, no statistical data exists to determine whether this notable growth will continue after the pandemic ends. Barry van Wyk (2022) describes Instant Retail as a concept that enables offline stores to utilise their physical locations and leverage the Internet as a sales channel. Businesses visible on platforms like Foodpanda adopt this model, operating physical stores and offering online options for selection and purchase. Similar to the rising popularity of Foodpanda in Malaysia, in China, delivery services provided by platforms such as Ele.me and Meituan, which have been well-known since 2014, have become a way for people to escape the kitchen and manage their increasingly limited leisure time (Netease, 2022). Besides traditional catering, Ele.me and Meituan offer additional services, including the delivery of daily necessities and other supermarket products (Cnhubei, 2019).

In 2019, Ele.me had 200,000 supermarkets registered on its platform (Cnhubei, 2019). Worship (2022) referred to this as the online instant retail market. According to Yangtse (2020), citing Alibaba's Elderly Digital Life Report, the number of elderly Chinese people using the Internet increased by 27.9% during the pandemic, with the

order volume on Alibaba's Hema app surpassing that of people born between 1990 and 1999 and those born between 2000 and 2009.

The factors driving the increase in online retail spending among the elderly in China remain unclear. Specifically, this study aims to evaluate the performance of Gen Y and Baby Boomers in traditional e-retailing and Instant retail, as well as the factors influencing their usage (Table 1.1).

Table 1.1
Electronic retail behaviour

Perspective: Instant retail
Definition: Like the food panda, supermarket supplies, food, and medical supplies are delivered to customers' homes within half an hour.
Problem 1: It is not yet clear whether the high-frequency instant retail usage behaviour among the elderly during the pandemic will diminish after the pandemic. **Problem 2:** It is not yet clear whether the health benefits of instant retail during pandemics, such as the recent global outbreak, still influence individuals to use this technology.
Objective: Identify the driving factors behind the elderly's use of instant retail and their usage status.

1.2.1.2 Offline Smart Retail

Elderly Chinese consumers face barriers to offline smart retail throughout the entire retail journey. Self-checkout systems enable consumers to use scanning devices to independently scan purchased products, pack them, and complete the payment process using computer technology without staff assistance (Lee et al., 2013).

Similar to the fully automated baggage check-in and ticketing processes at Malaysia's klia2 airport, some supermarkets in China have introduced unmanned self-checkout

systems (Yang & Kim, 2020). Consumers can independently tally the number of purchased items and calculate the total amount by scanning product barcodes at self-service counters (Thomas-Francois & Somogyi, 2023). Payment can be made through facial recognition, credit card, or mobile payment methods (Oltwater, 2022; Wang & Han, 2022).

Many elderly individuals stop using these devices due to inexperience, reduced dexterity, anxiety, and lower self-efficacy (Sina Mobile, 2019). Furthermore, staffed counters prevent the elderly from taking advantage of discounts offered on products in shopping malls (Sina Mobile, 2019). For example, a service fee of 20 RM is charged at the staffed baggage check-in counter at KLIA2 Airport.

There is sufficient reason to believe that self-service options help reduce contact and lower pandemic transmission. However, whether such self-service options will continue to be regarded as the ideal choice once the pandemic subsidies are withdrawn remains uncertain. During supermarket checkout, scanning errors can easily lead to incorrect prices and repeated or unsuccessful scans (Chineseherald, 2023).

The chance of elderly individuals recognising such errors is relatively low, which could lead to financial losses or trigger alert issues. It remains unclear whether this issue causes older adults to feel more financially at risk or if it acts as a barrier that prevents them from using the technology. The study aimed to identify the usage of self-checkout systems by Generation Y and Baby Boomers, as well as the factors influencing their use (Table 1.2).

Table 1.2
Offline checkout behaviour

Perspective: Self-checkout system
Definition: Self-checkout systems enable consumers to use scanning devices to independently scan purchased products, pack them, and complete the payment process using computer technology, eliminating the need for staff involvement.
Problem 1: There is a lack of reporting on the self-service retail usage behaviour of the elderly. **Problem 2:** Some groups face higher barriers to using such technology than others, and it is unclear whether these barriers lead to their non-use of technology.
Objective: To identify the facilitators and barriers that influence their use of the Self-checkout system and to identify differences from other groups.

1.2.1.3 Artificial Intelligence Reply

Artificial intelligence (AI) has been incorporated into the retail sector to improve response times and enhance customer experiences. Unfortunately, some reports indicate that AI services can be seen as impersonal and lack interaction between consumers and businesses, especially in terms of post-sales support, which may affect the shopping experience and the post-sales service expectations of older customers.

For example, Blanche et al. (2020) highlighted the limitations of using robots as service response tools, including their inability to resolve complex customer issues and reduced efficiency in handling complaints. Robot services often lack emotional intelligence and cannot establish meaningful relationships with consumers, which can result in customer dissatisfaction and feelings of being undervalued. It is unfortunate that, in China, online consultation and after-sales services are being replaced by AI (Song et al., 2019).

It remains uncertain whether Chinese elderly consumers see this as impolite and disrespectful, especially those with slow typing speeds who cannot type, have poor eyesight, make spelling mistakes, or find it difficult to communicate with AI

technology (Ithome, 2021). Conversely, switching from AI responses to human services is challenging, even in voice-based telephone services, which can be complicated (Jinwan, 2022). Jinwan (2022) describes China's widely used intelligent response systems as pseudo-intelligence. The research aims to clarify how artificial intelligence application technology is utilised by two groups of people in online stores and face-to-face shopping, covering all aspects of pre-sales and post-sales (Table 1.3).

Table 1.3
Human-computer interaction

Perspective: Pre-sales and after-sales omni-channel artificial intelligence reply
Definition: Human-computer interaction refers to artificial intelligence's response to consumer communication behaviours in online stores and the use of supermarket robots to answer consumer queries.
Problem 1: There is a lack of reporting on the behaviour of older adults using human-computer interactions. **Problem 2:** Some groups face higher barriers to using such technology than others, and it is unclear whether these barriers lead to their non-use of technology.
Objective: To identify the facilitators and barriers that influence their use of Human-computer interaction and to identify differences from other groups.

1.2.2 Post-epidemic Problems

During the pandemic, older adults who have already used instant retail and offline self-service continue to utilise these technologies. In contrast, older adults who have not engaged with digital technologies are slower to adopt them. According to People News (2021), the frequency of older adults using digital technologies in healthcare, dining, entertainment, and property management is increasing. Nearly all older adults with experience in using these technologies have chosen to keep using them, demonstrating strong user loyalty (People News, 2021). Elderly individuals with mobility limitations

show a high acceptance of home service offerings, addressing their inherent need for services while they are unable to go out (People News, 2021).

This indirect evidence indicates that older adults have adapted to new retail-related operational behaviours and are engaging in remote activities to conserve energy. According to Yangtse (2020), citing Alibaba's Elderly Digital Life Report, the number of elderly Chinese people using the Internet increased by 27.9% during the pandemic, with order volumes on Alibaba's Hema app exceeding those of individuals born between 1990 and 1999, as well as those born between 2000 and 2009. Before and after the pandemic, the shift in older adults' attitudes from initial resistance to temporary acceptance raises a new question: whether they will continue to adopt new retail practices or revert to their original refusal (Table 1.4).

Table 1.4
Before COVID and after COVID, retail habits

Perspective: After COVID
Definition: Most older adults have had short-term use experiences during a pandemic.
Problem 1: Whether this experience is shared in Shanghai has not yet been confirmed. **Problem 2:** There is a lack of research confirming whether this experience is helping them establish intentions and behaviours for continued use.
Objective: Identifying the level of experience and the impact of experience on both Gen Y and Baby Boomers.

1.2.3 Demographic Problems

In China, Gen Y's movement restrictions imply they may lack sufficient time and energy for supermarket shopping. They are often responsible for caring for children and the elderly, as well as completing demanding tasks assigned by their organisation

(Hassan et al., 2023). It remains unclear whether this intense pressure hinders their ability to engage in face-to-face shopping and causes them to prefer instant retail.

Compared to younger people, older individuals' physical limitations restrict their mobility, and many are unable to participate in traditional offline shopping. Lw News (2022) states that elderly people in China face mobility challenges and find it difficult to complete tasks related to travel and shopping independently. Online retail within the new retail industry provides a shopping avenue that caters to their needs without the need to leave their homes.

At the same time, transportation poses another challenge for the elderly. While young people can drive, take taxis, or use public transport, older individuals often cannot drive, and taxi refusal is a common issue. Sun and Hu (2022) note that elderly Chinese people face difficulty accessing taxi services, as drivers are concerned about their health and often refuse to pick them up.

Generation Y and Baby Boomers share a common trait – they are not considered true digital natives, or, according to most researchers, they fall into the category of non-digital natives. Therefore, comparative studies between the two should aim to minimise the influence of behavioural habits from the outset. Combes (2021) and Looney et al. (2021) assert that Gen Y and Baby Boomers are not digital natives. Consequently, they may be more open to exploring what new retail can offer rather than dismissing it as the only option.

Additionally, with the widespread adoption of digital technology, older people face more digital barriers, such as ride-hailing platforms or scanning codes for mall entry

(Xinhua, 2020). It has not been reported whether these factors increase the willingness of elderly Chinese people to use online retail within the new retail industry (Table 1.5).

Table 1.5
Movement restrictions

Perspective: Movement restrictions on going shopping
Definition: Movement restrictions refer to the impact of physical factors and time conflicts that prevent individuals from reaching the supermarket.
Problem 1: Do the physical problems of the elderly make them more inclined to use new retail systems, especially instant retail and human-computer interaction? **Problem 2:** Does the busyness of Gen Y make them more inclined to use new retail systems, especially instant retail and human-computer interaction?
Objective: Identifying the level of movement restrictions and the impact of movement restrictions on both Gen Y and Baby Boomers.

1.2.4 Location Choose Problems

Although the pandemic is waning, other undeniable restrictions continue to grow and cannot be ignored. For instance, in some retail stores, people refuse to accept cash payments because they lack change. In certain stores, self-checkout systems have become the primary method, with only a few manual checkout options remaining. A smart city refers to the integrated use of digital technology in urban areas to increase capacity and optimise existing resources, adapting to the changing technological environment and consumer demands. Examples include a cashless society, ride-sharing services, and QR code-based ordering (Habib et al., 2019). Shanghai is the fastest-growing economic hub globally and one of the most densely populated regions (3926 people per km ^{2}) (Statista, 2023). Consequently, the development of a smart city may pose challenges for the elderly and serve as a catalyst for the widespread adoption

of digital technologies. These positive developments in Shanghai, China, could also lead to new social restrictions (Table 1.6).

Table 1.6
Social restrictions

Perspective: Smart City and the disappearance of movement control
Definition: A smart city refers to the comprehensive utilisation of digital technology in urban areas to expand capacity and optimise existing resources, meeting the dynamic technological context and consumer demands. Examples include a cashless society, ride-sharing services, and QR code-based restaurant ordering.
Problem 1: It is unclear how restrictive such smart cities will be, such as whether merchants will accept cash, whether people will be required to use ride-hailing apps, and whether meals must be ordered using iPads or mobile phones. **Problem 2:** Whether this restriction is a facilitator or a suppressor.
Objective: Identifying the level of social constraints and the impact of social constraints of shanghai.

1.2.5 Variable-related Practical Problems

1.2.5.1 HBM Model Variables

In China, the pandemic is considered a serious threat to people's health, and it is unclear whether the Perceived Susceptibility (PSU) and Perceived Severity (PSE) of the pandemic will affect people's behaviour in digital retail. Perceived health risk strongly motivates the adoption of protective measures during an H1N1 influenza pandemic (Prati et al., 2020; Park et al., 2010), SARS (Leung et al., 2003; Kim et al., 2015), the Pandemic (Wise, 2020; Qian, 2020; Kim & Kim, 2020), and dengue fever (Othman et al., 2019).

Whether new retail benefits health is crucial, especially for older adults. More studies confirm that the harm of the PANDEMIC to the elderly is far greater than to other

groups, as they have poorer physical resilience and lower overall levels of physical function (Shahid et al., 2020; Wei et al., 2020). Older patients tend to exhibit more significant underlying comorbidities and abnormal laboratory results compared to younger individuals (Wei et al., 2020). The older group faces a higher risk of acute respiratory distress syndrome (ARDS), acute cardiac injury, and heart failure; notably, the oldest patients experience more multi-organ damage (Wei et al., 2020).

Furthermore, perceived health risk significantly positively influenced the adoption of health-related technology systems (Alaiad et al., 2019; Wei et al., 2020; Zhao et al., 2018), as well as application technology systems that reduce health threats (C.C. & Prathap, 2020; Puriwat & Tripopsakul, 2021; Daragmeh et al., 2021). Hence, this study examines the effects of PSU and PSE on the PU (Perceived usefulness) of new retail. The study aims to identify the factors that motivate people to adopt new retail practices. As awareness of the pandemic in China and other countries grows, it remains necessary to verify whether it still influences the behavioural changes of Chinese people.

Summary above: Most importantly, as the pandemic becomes a thing of the past, it remains essential to assess whether older adults still perceive technological benefits for their health. In China, new pandemics, such as influenza A and B, are emerging as fresh concerns affecting people's safety (WHO, 2023).

1.2.5.2 UTAUT Model Variables

During the pandemic, more residents joined the e-retail consumer group. After the pandemic, further exploration is needed to understand whether calls from family and friends will prompt new consumer retail behaviours.

In China, opinions on the use of technology by the elderly are polarised, with both supporters and critics involved. Some studies suggest that China is working to improve the well-being of older adults through technological initiatives, encouraging them to become part of the technology user community (Sun et al., 2020).

However, some research suggests the opposite. For instance, studies indicate that low digital literacy among older adults makes them particularly vulnerable to scams, thereby contributing to the ongoing issue of internet fraud (Lei et al., 2022). Research on elderly fraud victims in China reveals that over 30% of targeted seniors suffer financial losses (Lei et al., 2022).

Kulviwat et al. (2019) affirmed that technology acceptance is shaped by individuals' perceptions and recommendations from influential people and consumers. Facilitating conditions are regarded as technological support through software or hardware components. Both variables are also commonly used by researchers to examine user technology acceptance. According to relevant scholars, social influences affect the implementation of protective behaviour (Ning et al., 2020) and the adoption of technological innovation (Doan, 2020).

Several studies have confirmed the significant impact of facilitating conditions across various contexts, including mobile apps (Palau-Saumell et al., 2019), internet banking (Yeoh & Chan, 2011), and distance learning (Rita et al., 2020). Additionally, the capabilities of individual mobile devices are also regarded as a research variable. A study by C.C. and Prathap (2020) indicated that mobile self-efficacy is a crucial factor in examining the implementation of health-related behaviours and digital technology adoption during the pandemic. As awareness of the pandemic in China and other

countries worldwide increases, it is important to verify whether it still influences the behavioural changes of the Chinese population.

Summary above: Divergent views on technology adoption and resistance call for new research to verify or challenge the signals older adults receive and their subsequent effects. Furthermore, Shanghai's position as China's leading economic hub prompts questions about whether it has fully adopted digital technology and equipped itself with relevant devices. This issue warrants further investigation.

1.2.5.3 TORAOA Model Variables

No research has confirmed whether older adults in Shanghai believe that new retail effectively ensures safety. In the past, the presence of viruses in courier packaging was not unfounded; it contributed to their transmission and spread. Additionally, it remains unclear whether factors such as human-computer interaction and self-efficacy continue to be barriers for older adults in using technology, even as the country makes significant efforts to simplify digital operations and older individuals gain more experience.

The report by PEOPLE APP (2021) revealed that nucleic acid tests for express goods in many regions of China were positive, and those who had close contact with the goods were quarantined. XHBY (2022) stated that delivery workers who had suffered from the pandemic visited 38 restaurants, supermarkets, and other retail establishments, completing more than 500 retail operations; the number of close contacts was impossible to count. Whether the retail industry's support for delivery services meets the safety standards expected by consumers has become one of the hot topics in China (NEWS.CN, 2022).

This study aims to identify consumers' perceived health benefits (PHB) of new retail during the pandemic and then examine how these health benefits contribute to the perceived usefulness (PU) of new retail. As awareness of the pandemic increases in China and other countries worldwide, it is important to confirm whether it still influences the behavioural changes among Chinese people. Many elderly individuals stop using these devices due to lack of experience, reduced dexterity, anxiety, and lower self-efficacy (Sina Mobile, 2019). Additionally, staffed counters prevent the elderly from accessing discounts offered on products in shopping malls (Sina Mobile, 2019).

Blanche et al. (2020) highlighted the limitations of using robots as customer service tools, such as their inability to resolve complex issues and decreased efficiency in handling complaints. Robot services often lack emotional intelligence and find it difficult to build meaningful relationships with customers, which can result in dissatisfaction and feelings of being undervalued (Blanche et al., 2020). In China, online consultation and after-sales services are increasingly being replaced by AI (Song et al., 2019).

Whether Chinese elderly consumers perceive this as impolite and lacking in respect remains unknown, especially for those with slow typing speeds, who cannot type, have poor vision, make spelling errors, or struggle to communicate with AI technology (Ithome, 2021). On the other hand, transitioning from AI responses to human services is not easy, even for voice-based telephone operations, which can be complex (Jinwan, 2022). Whether these factors have negatively affected the elderly's perception of new retail needs further investigation. Lifetimes (2023) reported that the elderly in China

often encounter online and offline scams, and they struggle to distinguish between fake news and genuine products.

Some Chinese consumers believe that retail services based on big data infringe on privacy, and catering retail services often incur additional delivery charges and higher prices. There is little research on how Perceptual barriers (PB) influence Chinese consumers of different ages in adopting new retail technologies, and whether these factors impact their perceived accessibility to new retail services. Empirical studies are needed to confirm this.

In China, questions are emerging about the usability of new retail. A key difference between traditional retail and new retail is how consumer data is acquired and used (Chatterjee et al., 2021). A survey of 387 respondents, conducted using PLS-SEM technology, found that concerns over data privacy and security affect consumers' perceptions of omnichannel benefits and their intentions to use them (Chatterjee et al., 2021).

Forty per cent of consumers are concerned about personal information leakage, which offers a new perspective on emerging retail in China. 21JINGJI (2022) reported that nearly 40 per cent of consumers are worried about the security issues related to big data and artificial intelligence in terms of consumer privacy. This study aims to examine the factors of PB that influence consumer usage behaviour and to clarify the impact of PB on perceived usefulness (PU).

Summary above: This study aims to offer further insights into the limitations of new retail, especially for older adults. This includes addressing needs related to self-efficacy, limited support in pandemic control, and difficulties in human-computer

interaction with artificial intelligence services. The study seeks to determine whether these barriers have been addressed and overcome by digital technology developers in smart supermarkets, and whether Gen Y and Baby Boomers see them as obstacles.

1.2.6 Research Gap

Research on the use behaviour of new retail in China after the pandemic period lacks theoretical integration. During the pandemic, the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT) have been applied to study the effects of the pandemic on mobile payment (Zhao & Bacao, 2021) and Google Met adoption (Al-Maroof et al., 2020). Furthermore, the Health Belief Model (HBM), proposed to explain people's behaviour regarding health issues, has also been utilised by researchers to justify the influence of the pandemic on contactless technology systems acceptance (Champion & Skinner, 2008; Huang et al., 2020; Daragmeh et al., 2021; Sreelakshmi & Prathap, 2020).

However, these relevant prior studies only combine HBM with Expectancy Disconfirmation Theory (EDT), TAM with EDT, or UTAUT with EDT. Puriwat and Tripopsakul (2021) affirmed that, due to minimising physical contact among people in daily life to control the spread of the pandemic, acceptance of contactless technologies and digital transformation has increased. Unfortunately, the impact of post-pandemic usage behaviours—whether reverting to pre-pandemic behaviours or continuing with current practices—remains largely unstudied. It is also unclear whether individuals perceive these as means to prevent future pandemics. Based on these research theories, the researcher constructed several independent variables for investigation, such as perceived susceptibility, severity, benefits, barriers, ease of use, usefulness, health motivation, social influence, and facilitating conditions. Cham et al. (2022) propose a

theory of resistance among older adults (TORAOA) to identify factors contributing to their reluctance to adopt technology.

This study aims to incorporate this theory to explain refusal factors, including Digital Equipment, Perceived Financial Cost, Privacy Risk, and Perceived Self-Efficacy. This research will integrate the theory as a new avenue for investigation.

Theoretical Gap: Prior studies rarely integrate UTAUT, HBM, and TORAOA to analyse different generational cohorts comparatively.

Population Gap: Few studies specifically compare Gen Y with Baby Boomers regarding their post-pandemic adoption of digital retail services.

Contextual Gap: There is a limited amount of empirical evidence from the high-density urban environment of Shanghai regarding generational differences in technology acceptance.

1.3 Research Questions

Because the problem statement mentions several unidentified events, it is important to develop a clear research question to clarify the overall direction of the study. The study is mainly designed to answer the research questions listed below:

Main research questions

a) How do health-related perceptions (from HBM model)(susceptibility, severity, health benefits) influence perceived usefulness among Gen Y and Baby Boomers?

b) How do resistance-related perceptions (from TORAOA) (digital equipment, economic costs, privacy risks, self-efficacy) influence perceived barriers among Gen Y and Baby Boomers?

c) How do factors (from UTAUT)(social influence, perceived usefulness, perceived barriers) influence intention to use among Gen Y and Baby Boomers?

d) How do factors (from UTAUT and HBM)(experience, facilitating conditions, intention to use) influence using behaviour among Gen Y and Baby Boomers?

e) Whether perceived usefulness has a mediating role between perceived barriers and intention to use among Gen Y and Baby Boomers?

f) What are the differences in the variables constructed above between Generation Y and the baby boomer generation?

Sub research questions

How do health-related perceptions (from the HBM model)(susceptibility, severity, health benefits) influence perceived usefulness among Gen Y and Baby Boomers?

- **RQ1:** In the post-pandemic period, does Baby Boomers' and Gen Y's perceived susceptibility to the pandemic still affect their perceived usefulness of new retail technologies?

- **RQ2:** In the post-pandemic period, does the perceived severity of the pandemic still affect the perceived usefulness of new retail technologies for Baby Boomers and Gen Y?

- **RQ3:** In the post-pandemic period, do the perceived health benefits of Baby Boomers and Gen Y regarding new retail technologies still affect their perceived usefulness?

How do resistance-related perceptions (from TORAOA) (digital equipment, economic costs, privacy risks, self-efficacy) influence perceived barriers among Gen Y and Baby Boomers?

- **RQ4:** In the post-pandemic period, do the digital equipment needs of Baby Boomers and Gen Y to the new retail still affect their perceived barriers to new retail technologies?

- **RQ5:** In the post-pandemic period, does the perceived financial cost of Baby Boomers and Gen Y to the new retail still affect their perceived barriers to new retail technologies?

- **RQ6:** In the post-pandemic period, does the privacy risk of Baby Boomers and Gen Y to new retail still affect their perceived barriers to new retail technologies?

- **RQ7:** In the post-pandemic period, does the perceived self-efficacy of Baby Boomers and Gen Y to the new retail still affect their perceived barriers to new retail technologies?

Does perceived usefulness have a mediating role between perceived barriers and intention to use among Gen Y and Baby Boomers?

- **RQ8:** In the post-pandemic period, do the perceived barriers of Baby Boomers and Gen Y to the new retail still affect their perceived usefulness of new retail technologies?

- **RQ9:** In the post-pandemic period, do the perceived barriers of Baby Boomers and Gen Y to the new retail still affect their intention to use new retail technologies?

How do factors (from UTAUT)(social influence, perceived usefulness, perceived barriers) influence intention to use among Gen Y and Baby Boomers?

- **RQ10:** At a moment in the post-pandemic period, do the movement restrictions of Baby Boomers and Gen Y still affect their intention to use new retail technologies?

- **RQ11:** At a moment in the post-pandemic period, does the social influence still affect Baby Boomers' and Gen Y's intention to use new retail technologies?

- **RQ12:** In the post-pandemic period, does the perceived usefulness of Baby Boomers and Gen Y to the new retail still affect their intention to use new retail technologies?

How do factors (from UTAUT and HBM)(experience, facilitating conditions, intention to use) influence using behaviour among Gen Y and Baby Boomers?

- **RQ13:** In the post-pandemic period, will the facilitating conditions of the new retail still affect Baby Boomers' and Gen Y's intention to use new retail technologies?

- **RQ14:** In the post-pandemic period, does the intention to use the new retail still affect Baby Boomers and Gen Y using the behaviour of new retail technologies?

- **RQ15:** In the post-pandemic period, does the experience of technology usage affect Baby Boomers and Gen Y in their use of new retail technologies?

Whether perceived usefulness has a mediating role between perceived barriers and intention to use among Gen Y and Baby Boomers?

- **RQ16:** Do the perceived usefulness has a mediating role between perceived barriers and intention to use among Gen Y and Baby Boomers?

1.4 Research Objectives

This study aims to better understand the factors that influence the intention to use and actual usage of new retail in China following the pandemic. Therefore, this research evaluates knowledge-based theories with statistical analysis to identify how various variables affect the intention to use and the behaviour of new retail. These factors include perceived elements (susceptibility, severity, health benefits, barriers, usefulness, financial cost, self-efficacy), experience, movement restrictions, social influence, facilitating conditions.

The standard variables mentioned lack engaging elements. However, combining enabling and inhibiting factors creates an interesting contrast. Furthermore, the imminent end of the pandemic suggests that people may no longer be motivated by safety concerns, which could discourage certain technologies due to safety issues.

This aspect requires further confirmation. Naturally, this study distinguishes between Generation Y and Baby Boomers. For example, older individuals may prioritise health and utilise online grocery shopping but might be hesitant to interact with e-commerce virtual assistants. The objectives of this study are outlined as follows.

Indeed, here are the research objectives derived from the research questions provided:

Main research objectives

Based on the research questions, the study aims to:

I. Examine how health-related perceptions (from HBM model)(susceptibility, severity, health benefits) influence perceived usefulness among Gen Y and Baby Boomers.
II. Investigate how resistance-related perceptions (from TORAOA) (digital equipment, economic costs, privacy risks, self-efficacy) influence perceived barriers among Gen Y and Baby Boomers.
III. Explore how factors (from UTAUT)(social influence, perceived usefulness, perceived barriers) influence intention to use among Gen Y and Baby Boomers.
IV. Assess how factors (from UTAUT and HBM)(experience, facilitating conditions, intention to use) influence using behaviour among Gen Y and Baby Boomers.
V. Determine whether perceived usefulness has a mediating role between perceived barriers and intention to use among Gen Y and Baby Boomers.
VI. Identify and analyze the differences in these variables between Generation Y and the Baby Boomer generation.

Sub research objectives

Examine how health-related perceptions (from HBM model)(susceptibility, severity, health benefits) influence perceived usefulness among Gen Y and Baby Boomers.

RO1: Assess the impact of perceived susceptibility to the pandemic on the perceived usefulness of new retail technologies among Baby Boomers and Gen Y.

RO2: Assess how the perceived severity of the pandemic continues to influence the perceived usefulness of new retail technologies for Baby Boomers and Gen Y.

RO3: Assess whether the perceived health benefits of new retail technologies still influence the perceived usefulness of these technologies for Baby Boomers and Gen Y.

Investigate how resistance-related perceptions (from TORAOA) (digital equipment, economic costs, privacy risks, self-efficacy) influence perceived barriers among Gen Y and Baby Boomers.

RO4: Assess the effect of Baby Boomers' and Gen Y's digital equipment needs on their perceived barriers to new retail technologies.

RO5: Assess how the perceived financial cost for Baby Boomers and Gen Y in the new retail environment affects their perceived barriers to new retail technologies.

RO6: Assess whether the privacy risk perceived by Baby Boomers and Gen Y in the new retail setting still affects their perceived barriers to new retail technologies

RO7: Assess the impact of Baby Boomers' and Gen Y's perceived self-efficacy in the new retail environment on their perceived barriers to new retail technologies.

Determine whether perceived usefulness has a mediating role between perceived barriers and intention to use among Gen Y and Baby Boomers.

RO8: Assess how the perceived barriers to new retail technologies for Baby Boomers and Gen Y influence their perceived usefulness of these technologies.

RO9: Assess the influence of perceived barriers to new retail technologies on the intention to use them among Baby Boomers and Gen Y.

Assess how factors (from UTAUT and HBM)(experience, facilitating conditions, intention to use) influence using behaviour among Gen Y and Baby Boomers.

RO10: Assess whether movement restrictions still affect the intention to use new retail technologies among Baby Boomers and Gen Y.

RO11: Assess whether social influence continues to impact the intention to use new retail technologies for Baby Boomers and Gen Y.

RO12: Assess how the perceived usefulness of new retail technologies for Baby Boomers and Gen Y influences their intention to use them.

Determine whether perceived usefulness has a mediating role between perceived barriers and intention to use among Gen Y and Baby Boomers.

RO13: Assess the influence of Facilitating conditions in the new retail environment on the intention to use new retail technologies among Baby Boomers and Gen Y.

RO14: Assess how the intention to use new retail technologies influences the actual usage behaviour among Baby Boomers and Gen Y.

RO15: Assess the impact of technology usage experience on the usage behaviour of new retail technologies among Baby Boomers and Gen Y.

Determine whether perceived usefulness has a mediating role between perceived barriers and intention to use among Gen Y and Baby Boomers.

RO16: Assess whether perceived usefulness has a mediating role between perceived barriers and intention to use among Gen Y and Baby Boomers.

1.5 Scope of the Study

This study examines respondents from Shanghai, China, comparing Generation Y (born between 1981 and 1996) and Baby Boomers (born between 1946 and 1964). It investigates their adoption of digital retail services, including instant retail, self-checkout systems, and AI-assisted customer services within the post-pandemic environment. The research explores factors influencing the adoption of new retail technology in China following the epidemic. Based on existing literature, independent variables such as fear, perception (susceptibility, severity, benefits, barriers, ease of use, usefulness), health motivation, social influence, convenience, and mobile self-efficacy are selected. Additionally, new variables are introduced: mobility restrictions (to examine their impact on technology adoption among the elderly) and experience (to assess whether the new retail experience during the epidemic has fostered long-term behavioural habits). The study focuses on Shanghai, which ranks first in retail among 20 Chinese cities according to Savills Research (2019). In 2020, total retail sales of consumer goods reached 1.59 trillion yuan, a 0.5% increase from 2019 (Xinhuanet), and many new retail outlets have opened, such as Alibaba Xianhe Supermarket, Starbucks Reserve Roastery, MAC Experience Centre, Dr Ci: Labo Spa,

Luckin Coffee, and others. The survey employs a self-administered questionnaire to randomly select respondents residing in Shanghai with adequate purchasing power.

1.6 Significance of the Study

This study is both practically and theoretically significant, offering insights into the implementation of new retail technologies in the post-pandemic era. It guides decision-making for retailers and policymakers and deepens understanding of consumer behaviour regarding retail technology adoption. The study mainly investigates the differences in consumers' intentions and behaviours towards various retail services, specifically online instant retail services, offline self-checkout services, and e-commerce intelligent assistant services. The research aim to explore how different independent variables affect the intentions and behaviours linked to these three service types.

1.6.1 Practical Significance

1.6.1.1 Business Maker

The findings of this study offer valuable insights and guidance for retailers and policymakers in understanding the factors that influence the adoption of new retail technologies, especially in the post-pandemic era. Based on the relationships between variables such as PSU, severity, benefits, barriers, and self-efficacy, stakeholders can develop targeted strategies to encourage the adoption of new retail methods and overcome potential obstacles. Notably, this study aims to differentiate between three distinct types of retail services, including online instant retail services, offline self-checkout retail services, and e-commerce assistant services. For example, a supermarket business owner could introduce a taxi service project for senior citizens,

ensuring smooth transportation between the supermarket and their homes. This not only generates additional income but also enhances services that meet consumer needs.

1.6.1.2 Human-Computer Interaction to Artificial Services

One potential conclusion from this study is that older adults may struggle to communicate effectively with e-commerce assistants, leading to inadequate feedback and poor after-sales service, which could discourage their use of these services. Therefore, this study suggests that businesses still require human staff for online consultation services rather than relying solely on artificial intelligence. Additionally, it proposes that the accessibility of AI services for employee support should be clearly indicated to facilitate easy access and utilisation. In response to the resistance observed among the elderly towards human-machine interactions, researchers are committed to prioritising human assistance over automated interactions for this demographic.

1.6.1.3 Supermarket Restrictions

Another research implication related to business management concerns safety measures. When businesses find that older and younger individuals are no longer worried about the pandemic and do not fear it, they may voluntarily stop safety measures such as wearing masks, unrelated to government mandates. This can lead to customers choosing other shopping venues due to the absence of masks, thereby impacting business revenue and the overall consumer experience. On the other hand, this restriction pertains to cash payments, traditional checkout services, and whether to introduce telephone shopping and delivery.

1.6.1.4 Promotional Fairness

Furthermore, many businesses have adopted self-service systems as their primary mode of service, which has led to human assistance becoming a paid option or being less available, neglecting the needs and experiences of specific groups. A straightforward example is Malaysia's KLIA 2 airport, where travellers can complete check-in and baggage drop-off using self-service kiosks. The number of staffed service counters has been significantly reduced to about two, with an additional fee of RM20 applied. As a result, this study highlights the limited use of self-service systems among the elderly. Business decision-makers need to consider the fairness of various checkout options to reduce consumer dissatisfaction.

1.6.1.5 Equal Opportunity

As shown in Figure 1.3, people can perceive that the operated service area is crowded. Older adults may spend more time and money due to inexperience or low self-efficacy, as with the new retail self-checkout systems. This provides businesses with a clear perspective for improvement, emphasising the importance of not overlooking individuals facing technological barriers. While researchers do not deny that additional human channels impose significant cost pressures, the ethical and caring nature of fairness is crucial for the increasingly expanding elderly population.

Figure 1.3 KLIA 2 Self-Service Check-In Service and Self-Service Luggage Drop by KLIA 2 (2023)

1.6.2 Theoretical Significance

1.6.2.1 Promoting and Inhibiting Factors

This study adds to the knowledge on consumer behaviour by analysing the effects of PSU, including its severity, benefits, and barriers, on customers' perceptions of usefulness and their willingness to adopt new products. It emphasises the psychological factors and motivations that shape consumer decision-making and adoption behaviour within the context of retail technology.

1.6.2.2 Gen Y And Baby Boomers

Focusing on the generational differences between Gen Y and Baby Boomers, this study provides insights into how different age groups perceive and engage with new retail technologies. Retailers must understand these differences to customise their products and strategies effectively to target and meet the needs and preferences of various consumer segments. As outlined by the STP marketing model (Segmentation, Targeting, Positioning), businesses need to identify their target customer groups and develop strategies that address their specific needs to grow their market.

1.6.2.3 Theoretical Integration

This study combines multiple theoretical frameworks, including the HBM, the UTAUT, and TORAOA. Integrating these theories improves the understanding of the factors influencing the adoption of new retail technologies and provides a comprehensive framework for future research in this field. So far, no one has been able to offer a clear definition of the concept of new retail as it continues to evolve.

1.6.2.4 New Retail Multiple Perspectives

People's usage behaviours are challenging to define precisely. This study considers the context of the pandemic and provides a dual perspective on factors that might encourage or impede new retail. The intentions and behaviours related to usage are categorised into three distinct dimensions and analysed accordingly. This approach is innovative and has not been previously explored. The investigation into usage behaviour in this study focuses on three areas: the instant retail market, e-commerce assistants, and self-checkout systems.

1.7 Research Technical Route

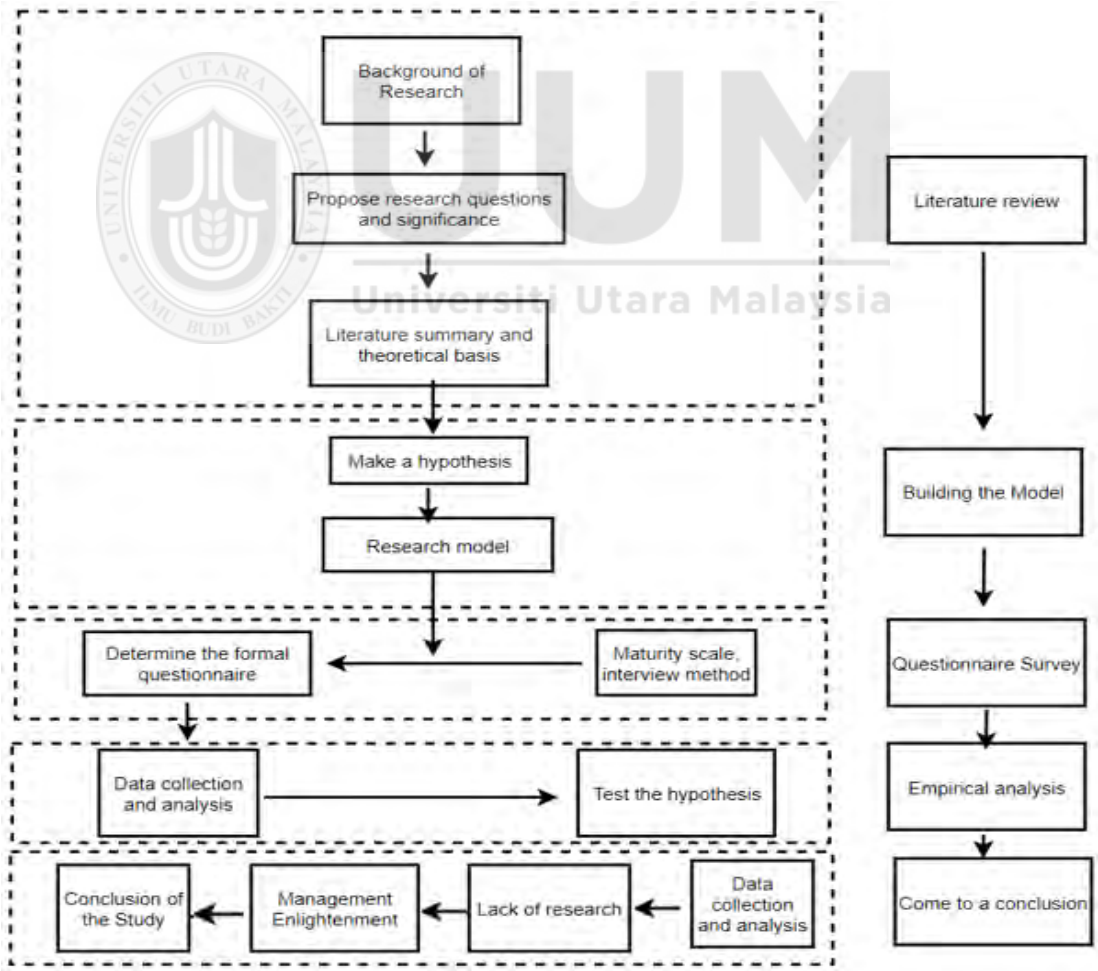


Figure 1.4 Research Technical Route by Author's Creation

1.8 Definition of Terms

a. New Retail

The term new retail has become more popular due to advances and innovations in electronic retailing. New retail is a unique business approach, different from traditional offline or online channels (Wei, 2021). The initial new retail ideas launched by Alibaba founder Jack Ma in 2016 included instant retail, offline shopping, online and offline returns, online payment on delivery, offline shopping online reviews, and offline shopping lines. Artificial intelligence is used to identify consumer purchase preferences, support online delivery, and improve online marketing efforts (Wei, 2021). He predicted that new retail, which combines online, offline, and logistical activities, will surpass e-commerce within the next ten to twenty years (Wei, 2021).

Artificial intelligence has gradually been integrated into the retail sector, enhancing and shaping the concept of modern retail as well as development patterns in both physical and online shopping. For example, artificial intelligence specialists are now utilised in online retail to assist customers with common issues during their purchase process and even to replace after-sales support staff (Luo et al., 2022). The adoption of various artificial intelligence technologies indicates their application in both new and traditional retail environments (Sharma et al., 2021). However, the term new retail was not clearly defined, leading to a range of interpretations.

A more detailed examination reveals that new retail is a retail business model that utilises big data and artificial intelligence (AI), which can enhance customer purchasing, operational efficiency, and corporate management (Lingyu et al., 2019). For example, artificial intelligence can more effectively deliver customised push alerts

to customers based on data mining technologies, offering them opportunities for products that they find hard to resist. In particular, new retail improves three key aspects of the customer's purchasing process. Its primary aim is to simplify the buying process and make it more convenient (Cai & Lo, 2020).

Consumers can use any payment method, including instant microloan services, bank cards, e-wallets, and face payments. The boundaries between the online and offline worlds are blurred in the new retail space, enabling retailers to offer consistent prices across all platforms (Luo et al., 2022). Through internet channels, consumers can quickly find details about various supermarket products, including type, price, shelf life, production location, and store hours. If they do not need to buy something immediately, they can order online and have it delivered to their chosen location (Luo et al., 2022). Consumers gain certain advantages. Busy shoppers can avoid long queues and the hassle of carrying bulky shopping bags thanks to the seamless integration of online and offline experiences (Wang, 2021).

The term new retail refers to aspects of electronic retailing that include last-mile logistics and distribution, electronic payment systems, and online purchasing (Wei, 2021). Therefore, considering new retail as online retail is not incorrect. They have an inclusive connection. It also encompasses Near Field Communication payment methods, which enable customers to use QR codes or barcodes on the Internet for product inquiries about prices, manufacturing schedules, new releases, and authenticity verifications (Van Doorn et al., 2017). An alternative perspective suggests that new retail represents a technological advancement of in-person retail services.

This research presents the idea of new retail, which merges self-service with artificial intelligence. Lowe et al. (2019) point out that self-service is growing in modern consumer interactions. It provides a practical way to reduce congestion in urban services (Shi et al., 2020). Enabling customers to take part in the service process lowers business costs and enhances service quality (Roy et al., 2018). Consumer needs have become clearer, and they have less time to compare and search for products. Retail store self-service technologies involve a comprehensive integration of multiple technologies, such as mobile wallets (Singh & Singh, 2020), artificial intelligence systems (Pillai et al., 2020) for problem-solving, self-checkout machines with visual capabilities (Bulmer et al., 2018), handheld scanners (Marzocchi & Zammit, 2006) for product scanning, and service robots for assistance and information exchange (Van Doorn et al., 2017). These technologies support customers at various stages of their grocery shopping, including locating specific products, obtaining relevant product information, and providing convenient checkout options. This technological combination is widely adopted in industrialised countries and some developing nations and is not restricted to any particular retail brand or service provider (Grewal et al., 2020).

This implies that emerging nations such as China must adopt this technology to become developed countries. Various factors, including age, gender, income, peer pressure, education level, perceived complexity, and security concerns, influence the uptake of these technologies (Shin & Perdue, 2019; Sharma et al., 2021). In this context, this research aims to identify which technologies individuals commonly use, why they do so, and whether they resist using them.

The retail sector involves more than just selling goods; it also includes interactions with customers and businesses. Berman and Evans (2001) define retailing as a commercial activity that encompasses both selling products and services to end consumers. As digital technology advances, services are shifting from traditional human interactions to non-human alternatives, particularly in retail. For example, over 80% of retail services in the United States are influenced by artificial intelligence technology (Alva, 2021).

The retail sector's expenditure on replacing human services with intelligent technology has reached an astonishing $7.3 billion (Swinhoe, 2021). Although countries and regions have not yet fully adopted this technology, the use of artificial intelligence for service delivery is rapidly growing. The artificial intelligence service market in retail is forecasted to reach $55.8 billion by 2028 (Edwards, 2021). In this study, artificial intelligence services refer to AI-powered online services, which are widespread across the Chinese internet landscape. However, there remains scope to improve how these AI-powered services meet consumer demands. While AI systems that respond to consumer requests are one aspect, other elements of artificial intelligence also require enhancement (Harris, 2020; Sinha & Lu, 2019; Lu & Sinha, 2023).

It would be too broad to examine all new retail perspectives, so this study selected three common perspectives: the Instant retail market, e-commerce assistants, and self-checkout systems.

b. Perceived Susceptibility

PSU is defined as the assessment of health-related risks. It is also known as perceived vulnerability or perceived likelihood. Furthermore, PSU is regarded as a perceived

threat and is a key factor in predicting human health-related protective behaviour (Paige et al., 2018). Similarly, Prati et al. (2010) suggested that PSU influences public behaviour when faced with health-related issues. In the context of PSU, individuals believe that engaging in certain behaviours may lead to health problems (Gaube et al., 2019). The outbreak of the pandemic has been shown to impact PSU and the public (Dryhurst et al., 2020). Therefore, people's perceived vulnerability influences their attitudes and preventative actions (Huang et al., 2020).

c. Perceived Severity

PSE, a measure of the importance of health-related effects, is a method for predicting potential outcomes of a specific situation or behaviour (Tweneboah-Koduah, 2018). The spread of the pandemic across China creates a unique environmental emergency, and people's food shopping behaviours indicate how they might respond to that situation. Additionally, PSE reflects an individual's evaluation of the negative or harmful effects of a particular action, according to Gaube et al. (2019). Their interactions with service providers and their financial payments could accelerate the epidemic's spread and cause further physical harm.

According to some studies, the virus or its effects influence how seriously the community perceives the epidemic (Dryhurst et al., 2020). Because of this, individuals might alter their behaviour to prevent the pandemic from taking hold in their bodies as soon as possible. Previous research by Ahadzadeh et al. (2015) and Tweneboah-Koduah (2018) suggests that PSE is perceived as a health risk, influencing public opinion.

d. Perceived Health Benefits

A person's perception of the benefits or positive effects of a specific preventive action is known as PHB (Farah, 2017). This view is quite common regarding technology use but often leads people to focus their efforts on using it more effectively for better health outcomes. According to Farah (2017), perceived benefits are people's favourable opinions about using technology systems for health-related issues. This study mainly focuses on how older adults regard specific technology use as having a positive impact on reducing the likelihood of illness.

For example, contactless payment methods can lower the public's risk of contracting a pandemic (Puriwat & Tripopsakul, 2021). Similarly, Karen (2011) explains how imagined rewards influence people's behaviour in defending against illness. That is, individuals are more likely to utilise technology when they find it performs very well in terms of personal safety. Therefore, Laforet and Li (2005) suggest that consumers' adoption of technological innovation systems to address health-related challenges is shaped by their perception of the benefits.

e. Perceived Barriers

PB refer to impediments or challenges that hinder the adoption of technological advancements or behavioural changes. They are seen as the opposite of perceived benefits. However, PB influence people's behaviour towards illness, such as perceived benefits (Karen, 2011). Factors contributing to PB include inconvenience, cost, language barriers, discomfort, etc. These barriers can prevent individuals from engaging in essential health-related actions (Mohamed et al., 2015). Similarly, Al-Tahitah et al. (2021) suggest that PB negatively influence people's preventive behaviour against the pandemic. In this study, PB include obstacles related to health

protection and those specifically linked to using new retail systems, such as self-efficacy, perceived financial costs, and perceived privacy risks.

f. Digital Equipment

Digital devices generally refer to gadgets capable of connecting to the internet and used for sending and receiving information. This study specifically concentrates on portable mobile devices and non-portable devices that support various electronic retail activities, such as smartphones, tablets, smartwatches, and computers (Editor, 2017). In addition to the devices themselves, the level of internet access and any latency issues encountered when accessing new retail platforms are also part of the investigation. Furthermore, this study examines personal devices and device coverage within retail stores, including mobile wallet payments, artificial intelligence systems for issue resolution, self-checkout machines with visual capabilities, and handheld scanners for product scanning.

g. Perceived Financial Cost

Perceived financial cost pertains to expenses associated with using mobile devices, including the purchase of smartphones, internet charges, fees for using e-retail platforms, potential price increases for products in online retail environments, and last-mile delivery costs (Tan et al., 2010). In this study, researchers aim to compare the costs linked to traditional face-to-face retail to determine whether perceived financial costs increase or decrease when using digital devices for electronic retail.

h. Privacy Risk

Researchers aim to determine whether customers perceive privacy risks tied to mobile apps provided by new retail systems. For instance, users' search activity in other applications might be intercepted and used to deliver targeted advertisements for specific products. These risks include the potential identification of search and browsing data, voice conversations, household head information, and other actions that could jeopardise consumer privacy (Lee et al., 2019).

This is often unavoidable. It should be banned even though it is legal. The study aims to find out if consumers think that the applications offered by modern retail systems pose privacy risks by examining customer attitudes. Instead of asking participants to choose between potentially safer and more harmful options, the study intends to provide a broad understanding of the issue. Notably, the current study does not focus only on users who have previously used these technologies or had direct evidence.

This suggests that the research also includes individuals who have never used the grocery app. The study covers consumer impressions and perceptions of those who have not yet engaged with these technologies. The goal of this research is to draw conclusions. Considering the viewpoints of both users and non-users, the study aims to provide a comprehensive understanding of consumer opinions and perceptions regarding the relevant technology.

i. Perceived Self-Efficacy

Mobile self-efficacy is the belief in one's ability to use a mobile device for specific activities (Keith et al., 2011). This refers to how individuals can exert effort to utilise internet shopping, intelligent assistants, and supermarket self-checkout systems. Similarly, Market et al. (2011) confirmed that mobile self-efficacy reflects a user's

capacity to use a mobile device to perform tasks and achieve objectives. It primarily emphasises the use of supermarket electronic shopping platforms and mobile payment solutions.

According to Mohammed-Issa and Khaled (2014), mobile self-efficacy refers to users' ability to utilise technological advancements related to mobile devices. This study aligns with this perspective. Furthermore, Hsu and Chiu (2004) combined Internet and mobile self-efficacy to describe the user's capacity to access the Internet and perform specific tasks using a mobile device. Consequently, several scholars have regarded mobile self-efficacy as a vital variable for analysing consumer use of mobile-related technological innovations. In this study, self-efficacy perception is not limited solely to mobile self-efficacy.

The research scope also explores consumers' perceptions of self-service devices offered by retail stores. Furthermore, self-efficacy includes the communication process between consumers and artificial intelligence (AI) online. The study also examines whether consumers believe they can communicate information effectively to AI and receive valuable feedback.

j. Perceived Usefulness

Customers' perception of PU relates to how effectively a modern technological system can enhance their work performance (Davis et al., 1989). Monsuwé et al. (2004) also claimed that PU depends on the user's experience with a specific technological system.

Several factors can influence PU, including experience, social influence, social norms, social pressure, social presence, attitudes, complexity, image, and demonstrability

(Lee et al., 2003). Therefore, PU is crucial for continuously evaluating consumers' intention to adopt innovative systems. In this study, PU is divided into two main aspects: its usefulness in preventing the spread of a pandemic and facilitating personal goals through new retail technologies.

k. Social Influence

According to prior scholars (Fishbein & Ajzen, 1975), social influence refers to a user's perception of external factors that recommend or persuade individuals to understand and adopt an innovation. Social influence includes the opinions of family, friends, or colleagues close to the user. It is a crucial factor that drives people's intention to adopt new technological systems (Venkatesh et al., 2012; Ofori et al., 2018). Therefore, social influence has been employed by researchers as an independent variable to investigate consumer acceptance of technology (Karahama & Limayem, 2000). Although social influence should be divided into three perspectives—instant retail, online consultation services, and offline self-service—to clarify the overall concept of new retail, this study rejects the division of new retail systems.

This study does not exclude the possibility that users' family members and friends might encourage them to use certain features of new retail, such as self-service, while discouraging online purchases and after-sales consultations. Some reports have indicated that older adults in China are susceptible to online sales frauds, such as costly but ineffective health products, resulting in financial losses (Liu, 2023). Accordingly, some family members of older adults refuse to allow them to make unplanned online purchases.

l. Movement Restrictions

This study's term mobility limitations does not relate to the movement restrictions imposed during the pandemic. Instead, it refers to the physical challenges faced by older adults that hinder their ability to walk or go out. According to Chan et al. (2021), older adults require technological interventions that can replace physical mobility and enable them to meet specific needs, such as enjoying scenic views from the safety of their homes.

m. Shanghai

China lifted its travel restrictions in December 2022 (Garry, 2023). Concerns about movement control are no longer at the forefront for most people. However, some local governments and companies have imposed minor restrictions due to the ongoing pandemic. These regional regulatory limitations are unavoidable. This study aims to determine whether respondents have faced different restrictions and if using internet shopping to buy goods has become necessary because of these limits.

For individuals, these restrictions include not only laws enacted by the government but also additional limitations imposed by businesses or the environment where they shop. The elderly, for example, might be unable to travel in taxis, and shops might offer many artificial intelligence services but relatively few manual ones. Retailers, of course, may refuse cash if they run out of change.

n. Facilitating Conditions

According to a previous study by Venkatesh et al. (2003), facilitating conditions are defined as resources, support systems, and infrastructure that promote or assist users in adopting technological innovations. Furthermore, Zhou (2011) confirmed that

facilitating conditions serve as essential knowledge and resources that influence users' adoption of technology. In addition, relevant literature (Rita et al., 2020; Farney, 2013; Palau-Saumell et al., 2019) suggests that facilitating conditions have a significant impact on users' acceptance and attitudes towards technological innovation systems. Consequently, several researchers have used facilitating conditions as the independent variable when evaluating consumers' acceptance of technology.

o. Experience

Experience refers to people's knowledge or understanding of specific things, which can come from learning, observation, or personal encounters (Kim, 2021). Experience allows individuals to respond and decide more effectively in particular settings, often resulting in correct actions that help them solve problems swiftly and accurately. In this study, experience includes three aspects: experience with online supermarkets, experience with e-commerce assistants, and experience with self-checkout systems.

P. Intention to Use

In this study, intention to use is categorised into three groups: intention to use A, intention to use B, and intention to use C. These represent the intention to use online supermarkets, e-commerce intelligent assistants, and self-checkout systems.

q. Using Behaviour

In this study, behaviour is also classified into three types: using behaviour A, using behaviour B, and using behaviour C. These represent the actual use of online supermarkets, e-commerce intelligent assistants, and self-checkout systems.

1.9 Chapter Outline

This chapter introduces Chapter 1, which provides background information and outlines problem statements. It also discusses the variables that affected the adoption of a new retail concept during the pandemic in China. Additionally, the research question and objectives are presented, followed by the scope of the study, the definition of key terms, research limitations, and a summary of the chapter.

Chapter 2 reviews relevant previous studies of the model or theory used in this research, including HBM, UTAUT, TORAOA. Based on the findings from the literature review, eleven independent variables were selected to examine the adoption of new retail during the COVID-19 pandemic. Additionally, the research model of this study is presented in this chapter.

Chapter 3 outlines the methodology for conducting this study and analysing the collected data. In this chapter, the research discusses several aspects, such as the unit of analysis, sampling procedures, data collection methods, pilot study, validity and reliability testing, and the statistical methods used for analysing the data and justifying the proposed hypotheses.

Chapter 4 details the data analysis and findings of this study. The collected data was analysed using descriptive statistics as well as reliability and validity tests. Additionally, multiple regression, normality tests, and correlation analysis were employed to evaluate the proposed hypotheses of this research. All analysed data and findings are discussed in relation to the relevant literature.

Chapter 5 summarises the findings of this study. It also discusses its contributions and limitations and offers recommendations for future research.

1.10 Chapter Summary

Chapter 1 introduces the study, focusing on the research background, objectives, and significance. It begins by highlighting the Pandemic's impact on consumer behaviour, especially in the retail sector. The chapter emphasises the need to understand consumers' perceptions and behaviours towards new retail systems, considering fear, susceptibility, severity, benefits, barriers, and social influence. It also introduces the concept of new retail systems, which include mobile devices, online platforms, self-service devices, and artificial intelligence. The chapter explains the importance of studying the adoption and use of these systems in the context of enhancing consumer experiences and enabling safe and convenient shopping during a pandemic.

Key constructs and variables related to consumer behaviour are defined and discussed, including PSU, PSE, PHB, PB, mobile self-efficacy, PU, social influence, intention to use, and actual usage behaviour. The chapter thoroughly describes the research scope, methodology, and limitations. It provides a clear overview of the variables, both independent and dependent, and affirms their definitions and dimensions within the context of the study. The chapter outlines the research scope, focusing on adopting and using new retail systems, specifically online supermarkets, e-commerce assistants, and self-checkout systems. It emphasises the importance of studying these technologies to improve consumer experiences and support safe, convenient shopping practices.

Regarding the research methodology, Chapter 1 briefly outlines the approach that will be used to investigate consumer behaviour towards new retail systems. It mentions using surveys or questionnaires to gather data and emphasises the importance of a quantitative analysis to explore the relationships between variables. The chapter also recognises the study's limitations. It notes that the research was carried out during the

pandemic, which may influence consumer perceptions and behaviours differently than under normal conditions. Additionally, it states that the research is limited to a specific geographical area or target population, which could impact the generalisability of the findings. Chapter 1 clearly defines the research scope, methodology, and limitations. It succinctly describes the variables to be examined and affirms their definitions and dimensions within the research context. This helps readers understand what will be analysed and what to expect from the study.

CHAPTER TWO

LITERATURE REVIEW

2.1 Introduction

Chapter two examines the relevant literature on the HBM model, UTAUT model, and TORAOA conceptual framework. The sources for this review include journals, articles, newspapers, the internet, books, and other materials related to the subject areas. Additionally, the research outlines how other scholars assessed factors influencing consumers' behaviour and supported the hypothesis introduced in Chapter One. Combining various theories, this research develops a new conceptual framework to replace the traditional theoretical model.

2.2 Post-Pandemic Retail Industry

The pandemic has prompted changes in business models and consumer demand across various industries, and the post-pandemic transformation of China's retail sector has not been fully detailed. Numerous studies have examined the impacts of the pandemic, such as in commerce (Salem & Nor, 2020; Prasetyo et al., 2021), education (Rizun & Strzelecki, 2020), payment and banking (Jonker et al., 2020), and health (Rahi et al., 2020).

Wang (2019) stated that the development of mobile and internet technologies supports innovative marketing strategies in China's retail industry. The new retail concept enhances consumers' shopping experience by integrating online and offline services.

Furthermore, real-time consumption has emerged within the new retail concept, allowing customers to purchase online and receive their goods on the same day as offline stores (Wang, 2019). The adoption of digital technologies in the retail industry is steadily increasing over time.

The global retail industry is experiencing a digital transformation (Reinartz et al., 2019; Ferreira et al., 2020; Castagna et al., 2020). Emerging technologies such as artificial intelligence (AI), cloud computing (CC), the Internet of Things (IoT), augmented reality (AR), big data analytics (BDA), and other digital strategies aimed at enhancing the well-being of consumers and retail businesses are permeating the sector, aligning with the principles of Industry 4.0 and culminating in Retail 4.0 (Har et al., 2022).

Standard digital technologies in brick-and-mortar supermarkets include shopping guide robots (providing product attributes, functionalities, and assisting with product location and price queries) (Ying et al., 2019), self-checkout systems (allowing customers to track purchased items and complete self-checkout independently) (Bulmer et al., 2018), quick response (QR) codes (enabling inquiries about production date, verifying authenticity, and inspecting products) (Khan et al., 2020), human-computer interaction (Van Doorn et al., 2017), handheld self-scanning devices (Marzocchi & Zammit, 2006), and AI services (Pillai et al., 2020; Pinochet et al., 2022). Research into digital technologies in the retail sector is increasing, aiming to highlight the impact of smart retail on stakeholders (Chang & Chen, 2021).

Because of technological progress and major changes in consumer behaviour driven by environmental factors, research carried out during the pandemic and earlier studies

might now be outdated. Studies that focus on specific groups, especially when comparing the elderly with others, are rare, emphasising the importance and worth of conducting such research.

2.3 China New Retail

2.3.1 Concept

New retail generally refers to the retail model that utilises digital technology within the retail industry, encompassing both online and offline activities. This study highlights three aspects of new retail: self-service technology, e-commerce assistants, and instant retail.

The combination of online, logistics, and physical marketing is the core idea of new retail (Jack Ma, 2016). New retail differs from traditional e-commerce. The integration of both channels represents a fusion state, as you have me and I have you (Hong, 2017). Both physical and online retail are exploring how to apply new retail concepts, where e-commerce creates an online and offline integration with logistics. New retail is also seen as a key milestone in the development of the online-to-offline (O2O) business model. In a previous study by Herhausen et al. (2015), channel integration required meeting two guidelines: accessibility and availability of information in the online store at a physical store, and accessibility and availability of physical store details at the online store.

Thus, consumers can access the store either from the physical store to the online store or from an online store to the physical store. According to Xu (2017), realising new retail requires technological innovation support and improvements in scientific and technological applications. This model uses data collected both online and offline to

enhance the operational efficiency of the retail market and improve consumer experience (Wang et al., 2019). The new retail targets middle-class consumers (Fan, 2019). Recently, middle-class consumers in Chinese society have been willing to spend more on valuable experiences and goods. The new retail market is estimated to exceed 1.8 trillion yuan in 2022 due to changing consumer behaviour (Hong, 2018). The emergence of new retail has significantly transformed living and consumption habits (Li, 2020).

The new retail differs from traditional and digital retail. It is a customer-focused retail model based on customer demand to develop marketing, sales channels, sourcing and production, supply chain, and product innovation (Zhang et al., 2018).

A few studies have demonstrated that the new retail concept is an updated version of the online-to-offline (O2O) business model, which digitalises traditional offline stores and utilises mobile technologies for ordering and payment (Chen, 2018). According to several studies conducted by other researchers, the new retail digitises traditional offline stores by applying more ICT, including cloud big data, computing, artificial intelligence, and mobile payment (Ding et al., 2018; Zhang et al., 2018). Marketers will not miss out on a significant portion of the offline retail market within the new retail concept. Furthermore, having an offline store that supports showrooming or webrooming helps marketers capture the entire retail market. For showrooming, consumers typically visit a store to examine the product before purchasing it online, knowing exactly what they want, and then buy online (Kang, 2018). Conversely, webrooming involves consumers searching for and confirming products online before purchasing in-store (Flavián et al., 2016). Since 2016, nearly 60 of Alibaba's Fresh

Hema stores have opened in China; they offer fresh food such as vegetables, seafood, and meat (Peterson, 2018; Mitchell, 2018).

Within the new retail concept, showrooming and webrooming offer multiple channels for retailers or marketers to reach consumers, as these behaviours are now standard shopping practices (Flaviá n et al., 2020). Consumers use various online sources to explore product information. According to relevant literature, integrating online and offline channels offers several benefits. These include improved customer attitudes towards stores and their perceptions of service quality (Pantano & Viassone, 2015), as well as enriched purchasing experiences (Bloom et al., 2017; Sit et al., 2018). Hur é et al. (2017) states that smooth channel integration boosts sales by increasing consumer satisfaction, loyalty, and positive word-of-mouth.

Furthermore, some previous literature confirmed that customer experience theory and management produce positive shopping outcomes and influence consumer shopping motivations (Harris et al., 2018). Rodr íguez-Torrico et al. (2017) and Verhoef et al. (2015) proposed that the shopping experience, through the integration of online and offline channels, helps consumers feel more perceptive. Enjoyable shopping feelings impact consumer satisfaction, experience, and loyalty towards the organisation (Lemon & Verhoef, 2016; Audrain-Potevia et al., 2013).

Additionally, numerous relevant studies have affirmed that positive shopping emotions enhance consumers' attitudes and purchase intentions (Chandon et al., 2000; Bicen & Madhavaram, 2013) as well as word of mouth (Clark et al., 2008; Chung & Darke, 2006). A prior study by Rej ón-Guardia et al. (2017) examined showrooming as a shopping trend. However, many other relevant pieces of literature (Fern ández et al.,

2018; Verhoef et al., 2007; Yadav & Pavlou, 2014) suggest that web rooming is also a growing shopping trend.

They described consumers as preferring the internet as a source of product information, while physical stores remained the primary purchase channels. The findings revealed by PushOn (2018) indicate that UK consumers favour web rooming over showrooming. Customers in Europe, in particular, use online browsing more often than visiting showrooms. As the Google Consumer Barometer (2015) stated, 33% of European consumers search for products online before purchasing them in physical stores, and only 10% engage in showrooming.

The new retail concept offers several advantages, including the integration of online and offline stores and logistics services. Gómez-Suárez et al. (2016) suggested that web rooming and showrooming enhance smart shopping perception and consumer feelings. The intelligent shopping perception encompasses time-saving, money-saving, and making the right purchase (Jang et al., 2017; Atkins & Kim, 2012; Gensler et al., 2017; Aragoncillo & Orús, 2018; Wollenburg et al., 2018; Flavián et al., 2016).

Therefore, consumers visit physical stores to browse for items and then purchase online to save time on queues. Additionally, consumers search for product-related information online and buy in a physical store, where they receive the product immediately and avoid delivery delays. Whether through webrooming or showrooming, consumers can verify that a product best meets their needs and shopping objectives. Previous research (Jang et al., 2017; Fernández et al., 2018) has shown that showrooming is linked to a stronger sense of financial saving compared to webrooming.

Customers can compare the top online merchants by price. Additionally, the extensive product information available on the internet helps consumers negotiate prices effectively with vendors. While consumers can find lower prices and save time online, the appearance of products and immediate possession are only available in physical stores. Flavián et al. (2020) affirmed that the internet or online channels are preferred searching channels for consumers, whereas consumers prefer to buy in physical stores. These preferences show that the new retail concept aligns with consumers' purchasing behaviour.

In the new retail concept, before buying a product online, consumers can search for relevant information and examine the product's quality and appearance in a physical store (Fernández et al., 2018). The online information includes prices, reviews from previous buyers, additional product details, and more (Flavián et al., 2020).

2.3.2 Why New Retail

2.3.2.1 Supermarket Service Efficiency

The self-service technology in new retail has enhanced service efficiency. As one of the most populous countries in the world, China faces widespread urban congestion (Peng et al., 2023). In supermarkets, consumers often wait in long queues, which significantly reduces service effectiveness. Self-service systems occupy minimal space, allowing consumers to scan and pay independently, thereby increasing service efficiency (Sharma et al., 2021) (Figure 2.1).

Figure 2.1 Transformation from Traditional Supermarkets to Self-Service Checkouts by Author

2.3.2.2 Supermarket Service Costs

Self-service technology in supermarkets has lowered service costs. In the past, supermarkets needed many staff to handle customer queries, checkout, product questions, and guidance towards targeted products (Slack et al., 2020). Sohu (2021) stated that supermarkets typically employ 30 cashiers, costing about 1.26 million RMB each year. Self-checkout devices in supermarkets cost around 10,000 RMB each, requiring four cashiers, with annual costs of roughly 370,000 RMB (Sohu, 2021) (Figure 2.2). This suggests that the performance of self-service technology is comparable to that of supermarket employees, with only initial purchase costs and very low ongoing maintenance expenses. Furthermore, it can be easily scaled according to the number of supermarket customers without concerns about excessive labour costs.

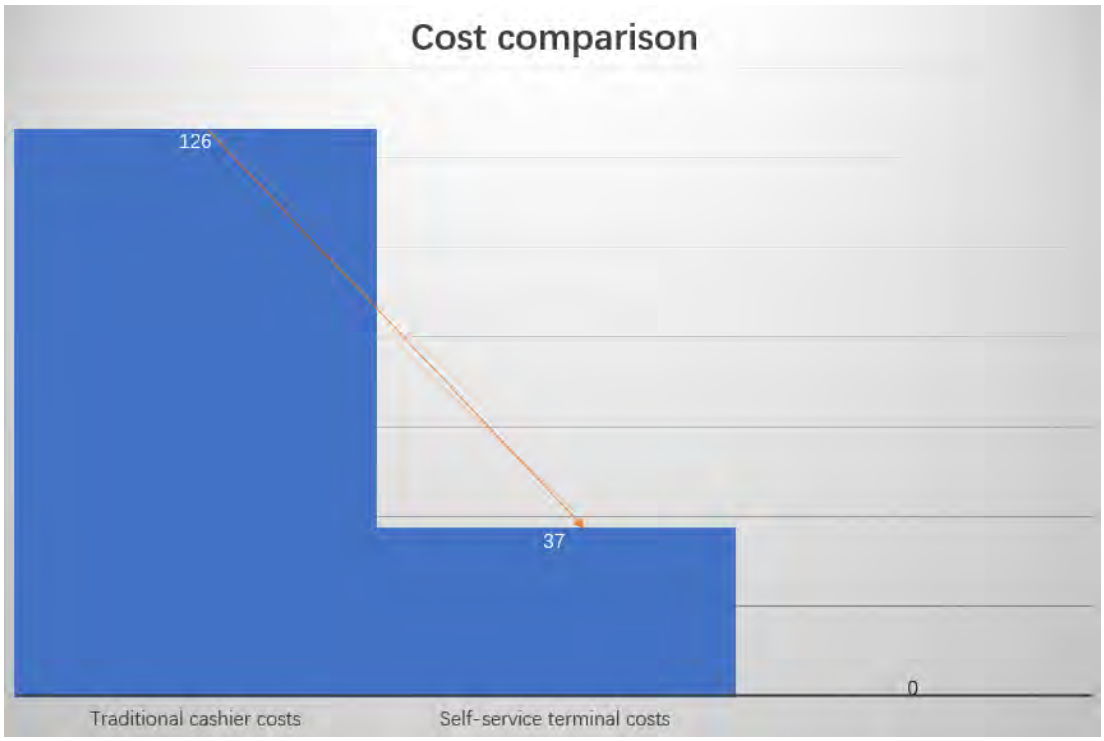


Figure 2.2 Traditional Supermarket and New Retail Self-Checkout System Costs by Author

2.3.2.3 Supermarket Service Experience

Self-service in supermarkets has improved the shopping experience for customers. According to Suddaby (2021), supermarket self-service, particularly self-checkout options, enables customers to choose and manage the checkout process, giving them the freedom to decide when to check out (Figure 2.3). This reduction in congestion leads to higher levels of satisfaction (Suddaby, 2021).

Figure 2.3 New Retail Supermarket Service Experience by Author

2.3.2.4 Supermarket Service Space

Compared to traditional manned service lanes, the self-checkout area lacks cashiers and many small items. As a result, consumers have more space to shop. In other words, the same checkout area can fit more self-checkout machines, reducing congestion of resources (Suddaby, 2021) (Figure 2.4).

Figure 2.4 Traditional Checkout Counters and New Retail Self-Checkout Terminals

2.3.2.5 Human-Machine Interaction Response Speed

The response speed of human-machine interaction is notably faster than that of supermarket service staff. Some researchers suggest that implementing AI responses instead of human customer service representatives in online shops is partly due to the immediate response time, which allows for the quick resolution of common queries (Kashef et al., 2021) (Figure 2.5).

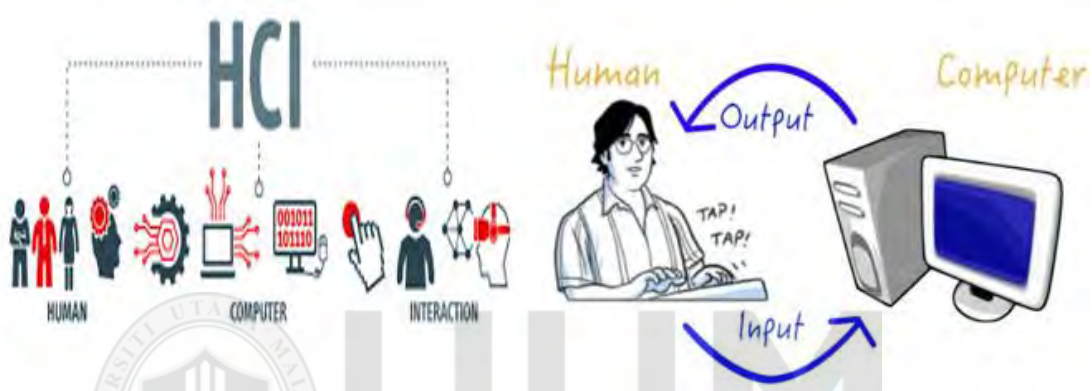


Figure 2.5 Human-Machine Interaction Response Flow

2.3.2.6 24-Hour Response

The benefit of human-machine interaction is clear in its ability to provide responses and answer questions outside of working hours, eliminating the need for service staff. China faces considerable work and career pressures (Lyu & Fan, 2022), which leave individuals with limited time to deal with personal life events when these conflict with work commitments. During their free time, retail employees may already be off duty. Therefore, human-machine interaction can help answer simple questions at any time, such as product usage instructions, country of origin details, and other common inquiries.

2.3.2.7 Response Consistency

E-commerce assistants can store more product information and deliver sufficiently accurate responses than service personnel. The way e-commerce assistants respond to questions is pre-determined (Wei, 2021). Therefore, they show a high consistency in language logic and sequence compared to less specialised service staff.

2.3.2.8 Response Accuracy

E-commerce assistants deliver more accurate information. Unlike humans, e-commerce assistants often fetch data from databases (Shafi et al., 2020). As a result, they are less likely to give customers incorrect details and may only offer outdated information.

2.3.2.9 Remote Shopping

Instant retail enables individuals to acquire products without physically visiting a supermarket. Foodpanda allows people to purchase items based on their needs from the comfort of their homes or workplaces, eliminating the necessity to visit specific locations (Brusch & Rappel et al., 2020).

2.3.2.10 Time Cost

Instant retail can cut down the time needed for shopping, especially for those who are far from supermarkets and have limited time. Taking Foodpanda as an example, the delivery rules often assign gig workers to those closer to the target supermarket (Basheer et al., 2022). As a result, they can quickly obtain the products customers want to buy from the supermarket and deliver them in the shortest possible time.

2.3.2.11 Purchase Guidance

One advantage of big data is that it helps better understand consumer needs than consumers themselves. Sometimes, people forget what products they want to buy in the supermarket. In instant retail apps, digital technology accesses the phone's memory and microphone to grasp consumer needs and offers targeted push services for specific products (Khaiyr & Rogermann, 2022). Individuals often see the products they desire prominently displayed within the app.

2.3.2.12 Remote Visualization

Instant retail offers remote visibility of products. Some consumers prefer to see the product before buying, which gives them a more complete understanding (Mondol et al., 2021). Virtual reality technology allows people to visualise products remotely before purchase.

2.3.2.13 Product Information

Instant retail offers product introductions, making it easier for consumers to compare products with their needs more intuitively. Previously, people's understanding of products in supermarkets was limited to the information provided on the packaging. With instant retail, customers can access detailed product descriptions from merchants, assisting them in selecting the appropriate products (Roggeveen & Sethuraman, 2020).

2.3.2.14 Reviews

Instant retail offers some consumer reviews for reference. In supermarkets, there is usually no bulletin board where people can learn about others' experiences with specific products. As a result, consumers might end up purchasing products that are

not well-received. Similar to online retail, instant retail provides descriptions of product information, including consumer reviews (Yang et al., 2021).

2.3.2.15 Price Comparison

People can compare the prices of target products across different instant retail stores, helping them choose the most cost-effective options. Price transparency is often a major benefit of e-commerce (Adler & Wohllebe, 2020).

2.3.2.16 Other reasons

Not many studies confirm whether older adults in Shanghai believe that new retail effectively ensures safety. In the past, the presence of viruses in courier packaging was not unfounded; it contributed to their transmission and spread. Furthermore, it remains unclear whether factors such as human-computer interaction and self-efficacy continue to be barriers for older adults in using technology, even as the nation makes significant efforts to improve the ease of digital technology use and as older individuals gain experience.

The report by PEOPLE APP (2021) revealed that the nucleic acid test for express goods in many regions of China was positive, and those who had close contact with the goods were quarantined. XHBY (2022) stated that delivery workers affected by the pandemic visited 38 restaurants, supermarkets, and other retail outlets and completed more than 500 retail transactions, making it impossible to track close contacts. Whether the retail industry supporting delivery services meets the safety standards expected by consumers has become one of the main topics in China (NEWS.CN, 2022).

This study aims to identify consumers' perceived health benefits (PHB) of new retail during the pandemic and then assess how these health benefits contribute to the perceived usefulness (PU) of new retail. As awareness of the pandemic grows in China and other countries worldwide, it needs to be verified whether it still influences the behavioural changes among Chinese people. Many elderly individuals stop using these devices due to lack of experience, reduced dexterity, anxiety, and lower self-efficacy (Sina Mobile, 2019). Furthermore, staffed counters prevent the elderly from enjoying discounts offered on products in shopping malls (Sina Mobile, 2019).

Blanche et al. (2020) highlighted the limitations of using robots as service response tools, including their inability to resolve complex customer issues and decreased efficiency in handling complaints. Robot services lack emotions and cannot build friendships with customers, which may lead to dissatisfaction and feelings of being undervalued (Blanche et al., 2020). In China, online consultation and after-sales services are being replaced by AI (Song et al., 2019).

It remains uncertain whether Chinese elderly consumers view this as impolite and disrespectful, especially those with slow typing speeds, poor vision, spelling errors, or difficulty communicating with AI technology (Ithome, 2021). Additionally, shifting from AI responses to human services is challenging, even for voice-based telephone systems, which can be complex (Jinwan, 2022). It is still unclear if these factors have negatively influenced the elderly's perception of new retail. Lifetimes (2023) noted that elderly people in China frequently encounter online and offline scams and struggle to identify fake news and counterfeit products.

This study aims to offer further insights into the limitations of new retail, especially concerning older adults. It focuses on addressing issues related to self-efficacy, limited support in pandemic management, and difficulties in human-computer interaction with artificial intelligence services.

2.3.3 Pandemic and Retail Behaviours

2.3.3.1 Impact of Pandemic on Human Behavior

The CDC (Centre for Disease Control) (2021) provides guidance for the public on preventing COVID-19 infection. The recommended practices are as follows: (1) get vaccinated; (2) wear a mask; (3) maintain social distancing of at least 1 to 3 metres; (4) wash hands frequently with soap or alcohol sanitiser; (5) cover coughs and sneezes with tissues; (6) clean and disinfect touch surfaces daily; and (7) monitor our health daily. According to Ferguson (2020), the most important behaviours for controlling the COVID-19 pandemic are hand hygiene and maintaining social distance. This view is supported by Ahmed et al. (2018), who found that influenza infection was reduced by 23% in crowded gatherings. Furthermore, adopting protective behaviours is essential to reduce the risk of COVID-19 infection (Jang et al., 2019; Everett et al., 2020).

2.3.3.2 Impact of Pandemic on Retail Consumer Purchasing Behaviours

Most of the time, people work and study from home. Consumers are also seeking products or services from home through online channels. As a result, new retail concepts that combine online and physical channels gained consumers' interest during the outbreak of the pandemic. Sayyida et al. (2021) revealed that online retail sales in Latin America, the United States, the United Kingdom, Germany, France, and Canada

have increased by around 10% to 15% during the pandemic. However, online retail sales are still lower than physical retail sales, accounting for only about 30% of total retail sales. Therefore, consumers might prefer web rooming, which allows them to check out products online and then purchase directly in physical stores to save time.

Besides this, consumers interact directly with products to boost satisfaction and confidence while shopping. So, According to Sayyida et al. (2021), customers preferred to purchase exclusively online and make transactions in webrooms during the pandemic. According to Yangtse (2020), citing Alibaba's Elderly Digital Life Report, the number of elderly Chinese people using the Internet increased by 27.9% during the pandemic.

2.4 Generation Y and baby boomer

2.4.1 The Impact of Physical Aging Differences on Technology Use

In the study of technology acceptance, generational differences, as a key moderating factor, have a significant impact on the formation of individual digital literacy and technological behaviour pathways. There are fundamental differences between the baby boomers (born 1946-1964) and Generation Y (born 1981-1996) (Britannica, 2025) in digital literacy structure, risk perception mechanisms and neurocognitive performance. The baby boomers display an operational approach centred on instrumental literacy, characterised by high reliance on offline channels, strong risk avoidance and heightened sensitivity to privacy risks (Kohlbacher, 2015). Neuroscience research indicates that the plasticity of their prefrontal cortex diminishes with age, leading to a notable decline in the efficiency of processing new technologies; increased activity in the amygdala intensifies fears of privacy breaches, while the

inertial structure of the basal ganglia stabilises, making it more challenging to adopt new operational modes (Lövdén et al., 2013).

In contrast, Generation Y demonstrates stronger strategic digital literacy, is able to collaborate across multiple platforms, possesses a high level of algorithm awareness, and has a need for immediate feedback (Venkatesh et al., 2022). Neuroimaging evidence shows that Generation Y exhibits greater activation in the multitasking area of the dorsolateral prefrontal cortex, and their nucleus accumbens responds significantly to immediate rewards, leading to an average purchase decision time of less than 8 seconds on social platforms (Telpaz et al., 2015). This difference provides neural support for subsequent behavioural path analysis. Therefore, in terms of physical development and ageing characteristics, Generation Y and the elderly display significant differences, which affect their use of technology.

2.4.2 A Global Perspective on The Segmentation of New Retail Behavior Groups

A comprehensive review of new retail development practices in major regions around the world shows that systematic differences exist between baby boomers and Generation Y regarding technology usage frequency, error rate, usage methods, and conversion efficiency. For example, in the North American market, the usage rate of self-service checkout systems among baby boomers is only 23%, with an error rate as high as 37%; whereas, the usage rate among Generation Y is 89%, and the average operation time is less than 90 seconds (MIT AgeLab, 2022). This trend is also evident in the European Union, where up to 45% of operations by baby boomers require manual assistance, while Generation Y prefers scanning codes and paying independently. In China's unique community group buying scenario, the baby boomer cohort has demonstrated a strong community learning effect due to the social support

structure, and the usage rate of new retail has risen from less than 20% before the pandemic to 41%, with the usage rate of voice assistants reaching 67%. Generation Y exhibits a very high adaptation rate to AR functions and tolerance for instant retail premiums, reflecting that this group's technology usage behaviour has become highly integrated into social scenarios and reward mechanisms.

2.4.3 Behavioural Restrictions on Two Groups of People and Promotion of New Retail

In China, Gen Y's movement restrictions imply they might lack the time and energy for supermarket shopping. They are often responsible for caring for children and elders and handling heavy tasks assigned by their unit (Hassan et al., 2023). It is uncertain whether this substantial pressure leaves them no time for face-to-face shopping and leads them to opt for instant retail.

Compared to younger individuals, older people's physical limitations restrict their mobility, and many cannot engage in traditional offline shopping. Lw News (2022) states that elderly individuals in China face mobility challenges and find it difficult to accomplish tasks related to travel and shopping independently. Online retail within the new retail industry provides a shopping channel that caters to their needs without the need to leave their homes.

At the same time, transportation poses another challenge for the elderly. While young people can drive, take taxis, or use public transport, older individuals often lack the ability to drive, and taxi refusal is common. Sun and Hu (2022) note that elderly Chinese people encounter difficulties accessing taxi services, as drivers are concerned about their health and frequently refuse to pick them up.

Furthermore, as digital technology becomes more widely adopted, older people face more digital obstacles, such as using ride-hailing services or scanning codes for mall access (Xinhua, 2020). It remains unreported whether these factors influence an increased willingness among elderly Chinese individuals to engage with online retail within the new retail industry.

The elderly have become more fashionable, adopting new technology. The pension replacement rate for most retirees in China is around 80% to 90%, and adequate pensions have alleviated their worries about basic material needs (People, 2016). Higher disposable income encourages the elderly to continually develop new forms of entertainment to fill the gaps in their lives. Consequently, they no longer resist digital technology and warmly embrace its advantages.

In China, online communication, instant retail, online dating, online news, online video, online finance, online travel services, and online medical service apps have been adapted into user-friendly versions for the elderly (Stdaily, 2021). Such products have become essential products to enhance everyday life and have rapidly spread among older adults. Mobile payments support consumer instant retail and self-checkout systems.

2.4.4 The Overall Shift In China's New Retail Behavior

The mobile payment intentions and behaviours of the elderly in China have evolved over time, shifting from collective resistance to collective acceptance due to social influence, perceived usability, and PEOU. Xinhua Net (2017) reported that China's mobile payment system is unfriendly to the elderly. The report highlighted that the difficulty of registering for mobile payments exceeds the technical knowledge of some

older adults. The elderly still value the benefits of a cash-based society. Compared with regular cash transactions, they find mobile payments, which require scanning a QR code and entering a PIN, too complicated and prone to errors (Xinhua Net, 2017). Those elderly individuals who hold these views tend to form groups to encourage others to resist mobile payment (Xinhua Net, 2017). However, such opposition did not last long, and calls for resistance diminished. Two years later, Xinhua Net (2019) reported an opposite perspective. Digital engagement, especially through social media, is quietly spreading among seniors, and the convenience of mobile payments is increasingly being explored and accepted. Therefore, this study is essential to provide the latest insights into new retail practices in developed regions of China.

Table 2.1
Generation Y and baby boomer difference

Problem 1: The plasticity of the prefrontal cortex of the elderly decreases with age, resulting in a significant decrease in the efficiency of processing new technologies, while Generation Y is better.
Problem 2: The inertial structure of the basal ganglia of the elderly is solidified, making it difficult for them to master and use new technologies, while Generation Y is better.
Problem 3: China's technology tends to be friendly to the elderly, the operation difficulty is reduced, and the social encouragement is increased, reducing the negative impact of the elderly.
Problem 4: The elderly have more free time and can go to the supermarket. But they need convenient transportation and the elderly can walk. Young people have greater work pressure and less free time.

2.5 HBM Theory

2.5.1 Conception

HBM was initially proposed by Rosenstock et al. in the early 1950s. According to Charles and Paschal (2015), belief is closely related to individual behaviour and socialisation. Champion and Skinner (2008) stated that HBM theory (Figure 2.1) is one of the well-researched and widely applied frameworks to explain behaviour and behaviour change in preventive healthcare programmes (Champion & Skinner, 2008; Huang et al., 2020; Jones et al., 2015). The HBM comprises six central components, which are outlined below. These six components are as follows (Karen, 2011; Al-Tahitah et al., 2021):

1. **PSU:** an individual's risk perception at a specific condition.

2. **PSE:** the seriousness perception of an individual associated with a specific illness or condition.

3. **Perceived benefits:** the believed benefits of applying specific action to reduce the risk of the severity or mortality.

4. **PB:** the potential factors that prevent people from taking particular health action, such as financial, physical and psychological costs.

5. **Health motivation:** the degree of energy to encourage people to practise specific strategies for health issues.

6. **Cues to action:** the factors that motivate or remind people to act.

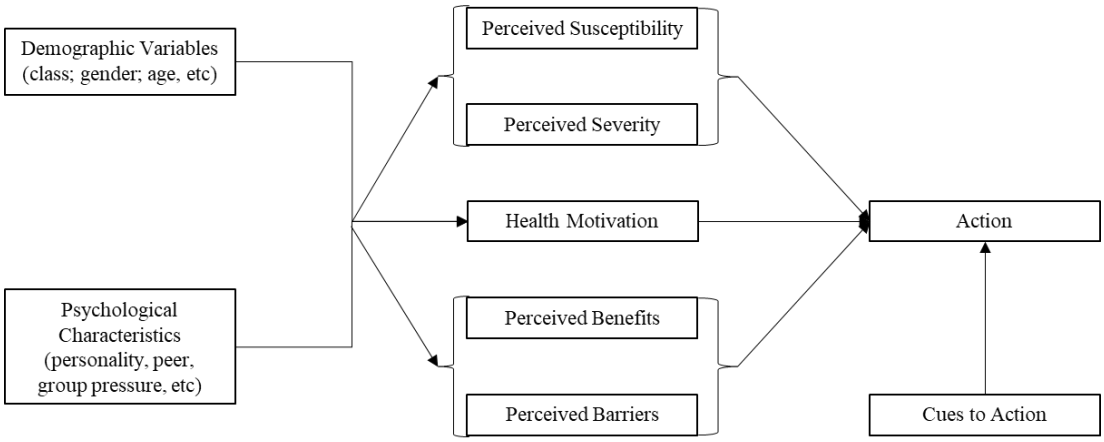


Figure 2.6 The HBM Model (Charles & Paschal, 2015)

2.5.2 Applicability of Theory

PSU and PSE are crucial in identifying ways to reduce harm through specific measures (Karen, 2011). However, individual perceptions of susceptibility and severity are highly subjective. PSU generally refers to the likelihood that a person will contract a disease (Gaube et al., 2019). Meanwhile, PSE is defined as an individual's belief that a negative outcome or harmful effect will result from behaviour. PSU is similar to perceived likelihood, while PSE is also known as perceived seriousness. For example, some people are willing to take preventive action if a health issue such as a fever is regarded as imminent and life-threatening.

However, some people view fever as a sign of immunity and believe that preventive action is unnecessary. Furthermore, this phenomenon influenced PSU, PSE, and PB of HBM in women and screening behaviour (Macpherson, 2000).

Perceived benefit and PB are vital in influencing people's behaviour towards a certain illness when they perceive its severity and susceptibility (Karen, 2011). In a study by Farah (2017), perceived benefits refer to positive behaviours based on an individual's

beliefs. PB is a negative factor that hinders an individual from adopting necessary prevention measures (Mohamed et al., 2015). Additionally, PB also relates to the anticipation of negative outcomes (Al-Tahitah et al., 2021). For example, during the pandemic outbreak, the belief that hand-washing and wearing masks are not effective infection control methods is regarded as a perceived barrier (Al-Tahitah et al., 2021). Several studies have shown that PB is key to predicting specific health behaviours (Norman & Brain, 2005; Carpenter, 2010). Furthermore, various factors influence cues to action, including illness, having a family member or friend diagnosed with a particular illness, or information provided by healthcare professionals or multimedia (Karen, 2011).

Several previous studies indicate that health motivation is defined as an individual's interest in their health (Kocoglu-Tanyer et al., 2020; Champion & Skinner, 2008). Moorman and Matulich (1993) demonstrated a link between health motivation and health behaviour. In the health field, positive effects on motivation, behaviour, and knowledge acquisition have been shown. Many researchers have used HBM to examine determinants influencing intention to use. Alaiad et al. (2019) also showed that HBM explains factors affecting the adoption of health-related technology from a health perspective.

People lacking adequate knowledge about the Pandemic and health motivation will be encouraged to use social media to enhance health awareness regarding the Pandemic (Al-Tahitah et al., 2021). HBM is also utilised for recognising consumer intentions towards digital technologies during the Pandemic (Walrave et al., 2020).

2.5.3 Why Use Post-Pandemic Retail

Although the pandemic is ending, similar outbreaks, such as influenza A and B, frequently occur in China (AP News, 2023). It is unclear whether older adults and Gen Y still see it as an effective measure to prevent influenza.

2.6 UTAUT Model

2.6.1 Conception

UTAUT was created to assess users' acceptance of new technology. Venkatesh et al. combined eight theories to develop the UTAUT model: TAM, IDT, TRA, MM, TPB, MPCU, and SCT. PE, EE, SI, and FC are the core components of the model (Shown in Figure 2.3), which are often used to study consumers' recognition and intentions to use various innovations. UTAUT is often found in fields with high digital technology demand, such as e-commerce, e-learning, e-banking, and e-government (Abu-Shanab & Pearson, 2007; Loo et al., 2009; Martins et al., 2014; Oliveira et al., 2014; Dečman, 2015).

PE is a user's perception of a technological device before and after use, mainly focusing on enhancing performance (Ofori et al., 2018). Relevant researchers have confirmed that PE and PU have similar effects on consumer behavioural intention and consumer behaviour.

In this regard, this study partially retains PE and PU, which are collinear. The performance of ICT products is highly associated with consumer usage intentions (Dulle & Minishi-Majanja, 2011). Among them, research on e-commerce performance and usage intention is more comprehensive (Ofori et al., 2018).

In the past, researchers classified the ease of using a particular technology as one of the EEs of that technology (Ofori et al., 2018). People generally do not reject easy-to-implement operations but are more inclined to resist techniques that are either impossible or require significant effort to accomplish (Venkatesh et al., 2012). In this regard, many researchers have found that EEs promote or inhibit the intention to use. Ofori et al. (2018) confirmed its consistency in digital marketing. Moreover, customer satisfaction with a technology innovation is also influenced by effort expectancy (Alwahaishi & Snášel, 2012). For example, users feel dissatisfied with mobile internet due to the small screens of mobile phones and inconvenient input methods for searching for information (Lee & Benbasat, 2004). Some studies stated that PEOU and EE did not differ significantly in their ability to influence and define dimensions of consumer use intention (Shin et al., 2010) and satisfaction (Lee et al., 2007).

Social influence refers to the tendency of users to be affected by advice or opinions from friends, relatives, and other close contacts. As a result, they develop attitudes of either accepting or rejecting a particular technology (Fishbein & Ajzen, 1975). Societal influence also plays a partial role in the adoption of new technologies (Venkatesh et al., 2012; Ofori et al., 2018). For instance, social influence that impacts customers' immediate retail behaviour comes from significant individuals such as family, friends, and colleagues, who can access information related to e-shopping (Lin, 2008; Clemes et al., 2014).

As Lian and Yen (2014) investigated, the intention among both the older and younger generations to purchase online was significantly influenced by social pressure. However, not all research shows a clear link between social influence and consumer

behavioural intentions. Shin (2009) and Ofori et al. (2018), in studies on e-commerce and e-wallet use, dismissed the impact of social influence.

Venkatesh et al. (2003) highlight that facilitating conditions are the resources, support systems, and infrastructure that encourage or assist users in adopting new technologies. The Internet requires users to possess relevant knowledge, technology, and the ability to pay applicable fees (Alwahaishi & Snášel, 2012). If users lack the necessary knowledge and resources, their adoption of the technology will be affected (Zhou, 2011). Infrastructure and the long-term cultural habits of consumers have influenced electronic payments (Tan, 2013). As the UTAUT model demonstrates, facilitating conditions significantly impact the actual use of consumer-to-consumer e-commerce websites (Ofori et al., 2018).

Behavioural intention refers to people's intent to promote a specific behaviour (Ofori et al., 2018). In related research on BI, there is a consensus that it points to the influence strength of using digital technology (Venkatesh et al., 2003). In UTAUT, significant findings showed that BI was more influential than FC (Ofori et al., 2018). A study by Tan (2013) demonstrated that behavioural intention significantly affected the actual use of English e-learning websites.

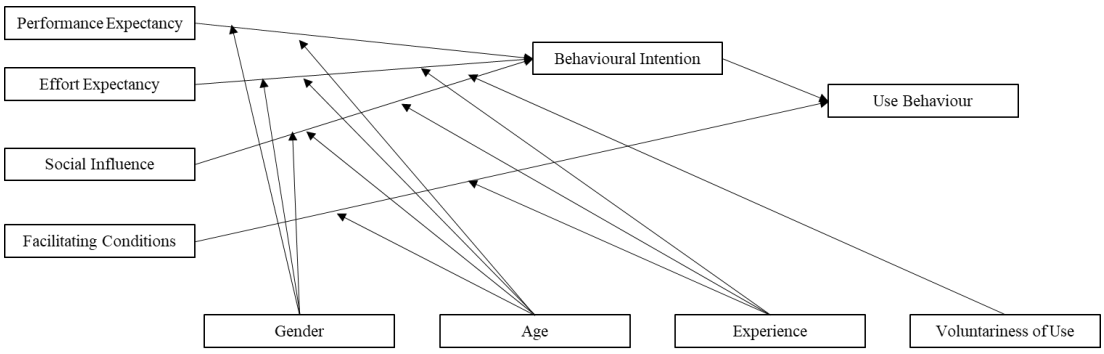


Figure 2.7 model (Venkatesh et al., 2003)

2.6.2 Applicability of Theory

This study examined various age groups, levels of usage experience, facilitating conditions, social influences, perceived availability, perceived usability, usage intention, and usage behaviour. The research logic aligns with the Unified Theory of Acceptance and Use of Technology (UTAUT), emphasising the influence of age differences, variations in facilitating conditions, social influence, and experience on usage intention and behaviour.

However, notably, this study aims to replace expected and effort expectancies with perceived availability and perceived usability. Some studies have shown that perceived availability is equivalent to expected expectancy, and perceived usability is equivalent to effort expectancy (Zhang & Poon, 2021). Therefore, age is divided into two groups for comparison within the new conceptual framework, while experience remains a key factor influencing behaviour.

2.6.3 Why Use in Post-Pandemic Retail

For elderly individuals, learning and using these technologies can be complex. They may exhibit poorer cognitive performance than other age groups (Huang et al., 2022). While their children may wish for them to embrace these technologies for convenience, especially for those with limited mobility, the children may also be hesitant because digital scams often target older people. E-commerce assistants may seem less helpful, as they can be less effective. Self-service terminals could cause repetitive scanning efforts and difficulties in packaging for them. Following the pandemic, they have gained experience, which may help them re-adopt these technologies more easily; however, further research is needed to confirm these speculations. Regarding experience, researchers see it as similar to someone wanting

to ride a bike but not knowing how; they cannot use the bike without intervention based on that experience. Therefore, behavioural intent does not fully predict behaviour; it requires intervention based on experience.

2.6.4 Reasons for rejecting UTAUT2

UTAUT2 is suitable for analysing users' behavioural intentions and usage behaviours of emerging systems (Venkatesh et al., 2012). However, this study did not employ this model as the primary theoretical framework. Hedonic motivation and habit both highlight the user's subjective experience. Nevertheless, this study does not examine whether users are willing to try new retail systems for the first time but aims to reveal how users modify their usage behaviours of popular systems such as online shopping, self-service checkout, and smart assistants due to their perception of infectious disease risks within the specific social and health context of the epidemic and post-epidemic period. Consequently, the focus of the research is on health risks and behavioural protection logic. Price value has also been modelled independently through perceived financial costs in this study. The decision not to utilise the UTAUT2 model is not because of its lack of explanatory power or empirical basis but is driven by a deliberate theoretical choice based on the specificity of the research problem, the non-overlap of variables, and the logical coherence of the overall model structure.

2.7 TORAOA

2.7.1 Conception

Cham et al. (2022) present a theory of resistance among older adults (TORAOA) to identify factors that lead to their reluctance to adopt technology. The research barriers

include three functional barriers: psychological and risk barriers (Figure 2.8). Cham et al. (2022) offer the following explanations for each variable.

- **Perceived complexity:** User's perception of the software's complexity.

- **Perceived incompatibility:** User's perception of inconsistency between the software and personal usage concepts.

- **Perceived cost:** User's perception of the costs associated with using the software.

- **Lack of Trust:** User's degree of distrust in the software.

- **Inertia:** User's perception of a lack of enthusiasm towards technology.

- **Technological Anxiety:** User's perception of psychological stress associated with using technology.

- **Privacy risk:** User's perception of the risk of personal information being stolen when using technology.

- **Security risk**: User's perception of the security of using technology.

- **Financial risk:** User's perception of the financial security associated with using technology.

- **Operational risk:** User's perception of risks encountered while using technology.

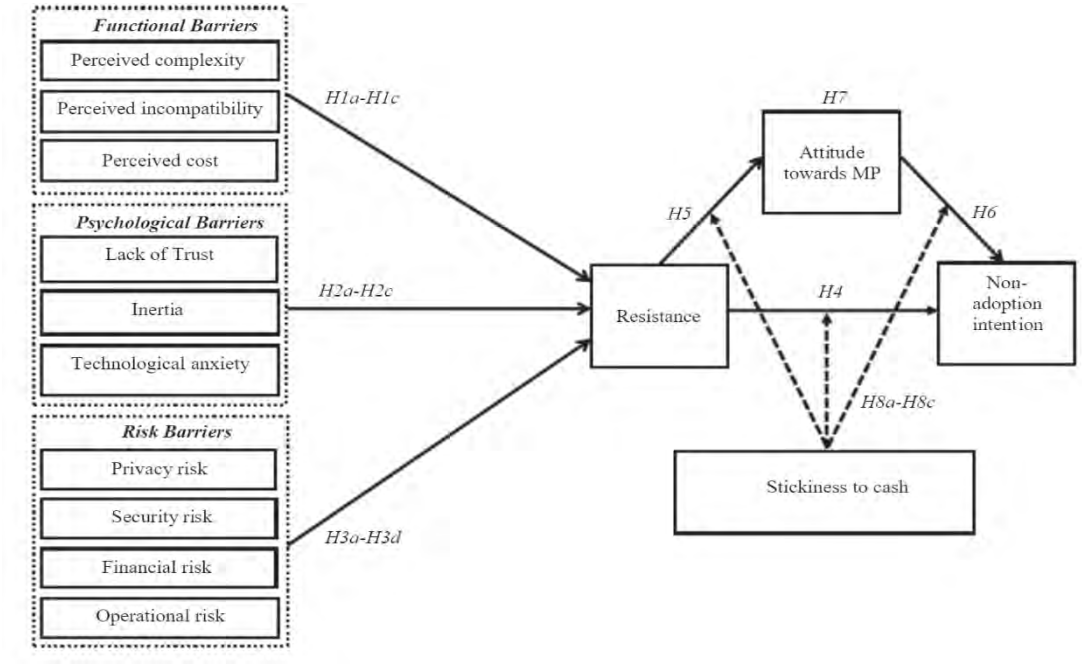


Figure 2.8 TORAOA by Cham et al. (2022)

2.7.2 Applicability of Theory

This study uses this theory to explain reasons for refusal, including Digital Equipment, Perceived Financial Cost, Privacy Risk, and Perceived Self-efficacy. These variables act as antecedents to perceived barriers. The research concentrates on older adults, in line with Cham et al. (2022).

2.7.3 Why Use in Post-Pandemic Retail

Following the pandemic, some elderly individuals have gained experience in using technology, potentially boosting their self-efficacy. Some reports indicate that Chinese seniors are being targeted by online fraudsters. Research on elderly fraud victims in China shows that over 30% of targeted seniors suffer financial losses (Lei et al., 2022). As a result, they may be more aware of the risks linked to certain new retail formats after the pandemic.

The elderly have become more fashionable, embracing technology. The pension replacement rate for most retirees in China is around 80% to 90%, and sufficient pensions have alleviated their worries about basic material needs (People, 2016). Higher disposable income encourages the elderly to explore new entertainment options to fill gaps in their lives. As a result, they no longer resist digital technology and welcome its benefits.

In China, online communication, instant retail, online dating, online news, online video, online finance, online travel services, and online medical service apps have been adapted into user-friendly versions for the elderly (Stdaily, 2021). Such products have become essential products to enhance life's enjoyment and have spread swiftly among older adults. Mobile payments supplement consumer instant retail and self-checkout systems.

The mobile payment intentions and behaviours of the elderly in China have experienced periodic changes over time, shifting from collective resistance to collective acceptance due to social influence, perceived usability, and PEOU. Xinhua Net (2017) reported that China's mobile payment system is unfriendly to the elderly. The report highlighted that the difficulty in registering for mobile payments often exceeds the technical knowledge of some older adults. The elderly remain attracted to the benefits of a cash-based society. Compared with regular cash transactions, they find mobile payments, which involve scanning a QR code and entering a PIN, too complex and prone to errors (Xinhua Net, 2017). The elderly who hold this view tend to form groups to encourage others to resist mobile payment (Xinhua Net, 2017). However, such resistance was short-lived, and opposition soon diminished. Two years later, Xinhua Net (2019) reported an opposite trend. Digital engagement, primarily

driven by social media, is quietly spreading among seniors, and the convenience of mobile payments has been continuously explored and recognised.

2.8 Conceptual Framework and Hypotheses

The theoretical framework is grounded in existing theories related to the study's hypotheses or objectives. Therefore, this framework guides the researcher in making an academic contribution within accepted theories (Adom et al., 2018). Many factors influence an individual's actions. Previous studies have incorporated a few models or theories to explore the intention to adopt a specific technology or service. The models or theories applied in earlier research are presented in this study.

To explain consumer behaviour towards new retail adoption during the pandemic, the researcher incorporates several theories to examine consumer behaviour. Firstly, the researcher chooses HBM, which is a model that is effective and commonly employed by researchers to study health-related cases. For example, Shahnaz et al. (2020) studied preventive behaviour during the pandemic using the HBM theory. Furthermore, TAM is also a favourable model for investigating new technology acceptance among consumers. UTAUT is also a favourable model that enables researchers to evaluate users' intentions towards specific technology. Numerous researchers have applied UTAUT to conduct studies on technological innovation, including online purchases (Doan, 2020), green banking technology (Boutera et al., 2020), and mobile applications for restaurant search and reservation (Palau-Saumell et al., 2019). Dwivedi et al. (2011) conducted a meta-analysis; they stated that the standard external variables of UTAUT that significantly affect behavioural intention include attainment value (AV), perceived risk, utility value (UV), trust, computer self-efficacy, attitude, PU, gender, income, PEOU, and experience.

2.8.1 Health Factor: Perceived Susceptibility

2.8.1.1 Conception

Perceived Susceptibility (PSU) is defined as a health-related risk assessment. Furthermore, PSU is regarded as one of the perceived threats, which is a crucial factor in predicting health-related protective behaviour in humans (Paige et al., 2018). Similarly, Prati et al. (2010) also suggested that PSU influenced public behaviour when dealing with health-related issues. Within PSU, people believe that their behaviour may cause health problems (Gaube et al., 2019).

2.8.1.2 Applicability of Variable

Dryhurst et al. (2020) proposed that the pandemic affected the public's PSU. Therefore, the attitudes or preventive actions of the public are influenced by PSU (Huang et al., 2020). Perceived threat is a key factor in determining health-related protective behaviour (Paige et al., 2018); it motivates behavioural changes (Kim & Song, 2017). During the outbreaks of H1N1 influenza and SARS, perceived health threat was used as a factor to predict behavioural changes in the public (Kim et al., 2015; Williams et al., 2012). Some previous studies used perceived health threats to examine the adoption of FinTech systems during the pandemic (Puriwat & Tripopsakul, 2021). Perceived health threats positively impacted patients' use of mobile health apps (Alaiad et al., 2019). Furthermore, the study by Shahnaz et al. (2020) showed a significant effect of perceived health threats on acquiring recommended protective actions. In new retail, remote methods such as instant retail, self-checkout terminals that eliminate contact with staff, and e-commerce assistants remotely receiving supermarket information are seen as effective ways to reduce the risk of illness.

2.8.1.3 Hypotheses development

Perceived Susceptibility (PSU) refers to individuals' assessment of their personal risk related to health threats. Previous studies have consistently shown significant links between perceived susceptibility and behavioural responses across different settings. For example, during the SARS outbreak, individuals' PSU greatly influenced their adoption of preventative measures (Leung et al., 2003). Similarly, research by Prati et al. (2010) demonstrated that PSU effectively influences public behaviour, guiding proactive health actions.

In recent years, PSU has been shown to positively influence the intention to use and actual adoption of mobile health technologies (Wei et al., 2020; Zhao et al., 2018; Dou et al., 2017). The perceived risk related to COVID-19 notably moderated consumer behaviours, increasing the likelihood of adopting online rather than face-to-face retail channels (Gao et al., 2020). During the early stages of the COVID-19 outbreak in Hong Kong, high levels of PSU (89%) and perceived severity (PSE, 97%) significantly shaped citizens' preventive behaviours (Kwok, 2020).

Hence, both perceived susceptibility and perceived severity are vital factors influencing preventive actions during pandemic outbreaks. Studies by Ning et al. (2020) have highlighted a link between PSU towards COVID-19 and demographic variables such as age. Huang et al. (2020) argued that PSU is essential in predicting individual attitudes and fostering proactive preventive behaviours. Kim and Kim (2020) further demonstrated that individuals who perceive a higher susceptibility to COVID-19 tend to actively engage in infection risk reduction behaviours.

As COVID-19 nears its final stages, similar pandemics like influenza A have continued to emerge in China (AP News, 2023). Consequently, this study suggests two possible scenarios: Firstly, a decline in COVID-19 threat perception may cause individuals to undervalue the usefulness of new retail technologies designed to reduce physical health risks. Secondly, even with a decreased perception of COVID-19 danger, elderly individuals might still see new retail technologies as valuable tools to manage ongoing risks from influenza and similar health threats.

H1: When using new retail e-commerce assistants, instant retail, and self-checkout systems, people's perceived susceptibility to the pandemic affects their perceptions of their technologies' usefulness.

2.8.2 Health Factor: Perceived Severity

2.8.2.1 Conception

Perceived Severity (PSE) is a health-related severity assessment and its potential effects (Tweneboah-Koduah, 2018). For example, people can quickly perceive that the pandemic poses a threat of death, especially among older individuals. Prior studies indicated that PSE could change and influence people's attitudes (Tweneboah-Koduah, 2018).

2.8.2.2 Applicability of Variable

The Pandemic's PSE leads to self-quarantine to reduce virus spread (Laato et al., 202). Prati et al. (2020) demonstrated that the adoption of preventive strategies during the H1N1 influenza pandemic in 2009 was influenced by public PSE. Some previous studies proved that the more severely individuals perceive a pandemic infectious

disease, the more actively they engage in health-related activities (Prati et al., 2010). For example, individuals with PSE of H1N1 influenza are more likely to perform hand hygiene daily (Park et al., 2010).

During outbreaks of the Pandemic, numerous studies found that people who perceive the high severity of the Pandemic are most willing to engage in preventive activities in their daily lives to reduce the risk of infection (Wise, 2020; Qian, 2020; Kim & Kim, 2020). Ning et al. (2020) investigated how PSE significantly influenced the adoption of protective behaviours during the Pandemic, which was confirmed by 94.4% of the respondents of this study. For example, people avoid gathering in crowds in high-risk areas during the Pandemic (Ning et al., 2020).

Besides that, PSE significantly influences people's attitudes towards dengue fever in Malaysia since dengue fever is a serious illness and can cause death (Othman et al., 2019). In this regard, people prefer remote retail and contactless self-checkout terminals as effective methods.

2.8.2.3 Hypotheses development

According to the Health Belief Model (HBM), people's perception of health threats—including perceived susceptibility and perceived severity—generally has a significant impact on their willingness to adopt and continue using related health technologies. Studies have shown that perceived severity (PSE) can notably influence users' intention to adopt and their actual use of mobile health technologies. For example, the widespread promotion of mobile medical devices and health monitoring applications mainly results from users' high awareness of the severity of the disease (Wei et al., 2020; Zhao et al., 2018; Dou et al., 2017).

Furthermore, during the COVID-19 pandemic, the public's perceived susceptibility (PSU) and perceived severity (PSE) increased significantly, and this perception directly triggered a large number of panic buying behaviours (Chua et al., 2021). In various countries' digital payment environments, this perception of disease severity has also been shown to encourage users to actively adopt contactless technologies such as mobile payments and e-wallets to minimise face-to-face interactions, thereby reducing the risk of contracting the virus (C.C & Prathap, 2020; Puriwat & Tripopsakul, 2021; Daragmeh et al., 2021).

Nevertheless, existing studies focus more on user behaviour during the outbreak and less on the post-epidemic context. As the COVID-19 pandemic is gradually brought under effective control, the public's vigilance and fear of the virus are steadily reduced, and they may regard the new coronavirus as a common flu-like illness, so its perceived severity may have significantly diminished (WHO, 2023). In particular, the elderly, who have experienced several years of epidemic prevention and control measures, may no longer see the virus as a serious health threat, thereby decreasing their perceived usefulness of new retail technologies such as self-service checkout systems, instant delivery, and artificial intelligence customer service.

Based on the above reasoning, this study hypothesises that in the post-epidemic era, people's perception of the severity of the disease may still influence their understanding and adoption of new retail technologies to some extent, particularly in specific scenarios such as self-service checkout, artificial intelligence customer service, and instant delivery. Users might tend to assess the effectiveness and value of these technologies based on their perception of health threats. Consequently, this study proposes the following hypothesis:

H2: When using new retail e-commerce assistants, instant retail, and self-checkout systems, the perceived severity of the pandemic affects people's judgments of the usefulness of these technologies.

2.8.3 Health Factor: Perceived Health Benefit

2.8.3.1 Conception

Perceived benefit refers to the advantage gained from using protective behaviours to reduce disease risk or from adopting a specific technology system. Laforet and Li (2005) suggested that perceived benefit is crucial in encouraging consumers to use a technological innovation system. Perceived Health Benefits (PHB) refer to the recognised advantages of new retail concerning health.

2.8.3.2 Applicability of Variable

Kolter and Armstrong (2003) discovered that consumers seek the benefits of products when making a purchase. A study by Liu et al. (2012) indicated that perceived benefit greatly influences individual attitudes. Similar findings were observed in various contexts, such as the intention to adopt online banking (Beatty et al., 2001; Lee, 2009), mobile banking implications (Akturan & Tezcan, 2012), the adoption of contactless payment technologies (Dong, 2020), and e-business usage (Zheng et al., 2006). This suggests that the health-promoting effects of new retail-related technologies will become a reason why people find them useful.

2.8.3.3 Hypotheses development

In the field of technology adoption in the post-epidemic era, organisations urgently need to strategically emphasise and effectively communicate the potential health

benefits of technological innovation to encourage consumers' willingness to adopt (Philips & Wright, 2009). This idea is well-founded, grounded in the deep insights of behavioural economics and health communication theory: by emphasising the preventive value of technological intervention, companies can bridge the gap between individual cognition and actual behaviour, thereby reshaping the consumption paradigm. However, previous research has identified a key challenge, which is that, due to the public's lack of detailed understanding of the consequences of epidemic infection, the perceived benefits of protective behaviour are often low (Jose et al., 2020). This cognitive bias not only arises from information asymmetry but may also be influenced by cultural and social psychological factors, such as the anchoring bias of risk perception, which is especially significant in cross-cultural comparisons, prompting us to deepen our exploration from the perspective of cognitive psychology.

Furthermore, the main advantages of contactless technology, such as greatly reducing the risk of virus exposure, have been identified as a key factor in its adoption (Puriwat & Tripopsakul, 2021). This finding aligns closely with the extended framework of the Technology Acceptance Model (TAM), where perceived usefulness is expanded to include health-related benefits, especially during crises, when it goes beyond simple functionality and becomes part of narratives about survival and well-being. However, as the epidemic gradually subsides, an unresolved academic question has arisen: Will consumers continue to see emerging retail technologies as a dependable safeguard for health? This uncertainty arises from the interaction of several factors, including the waning of habit inertia, the appearance of alternatives, and shifts in post-pandemic psychological resilience. Investigate the dynamic interplay between cognitive persistence and behavioural continuity. Only by doing so can the research go beyond superficial analysis and uncover the profound dialectical relationship between

technology and human well-being. This study suggests that older adults may still consider contactless services a meaningful benefit for managing influenza or other infectious diseases, as they tend to be more concerned about health (Guo, 2024). Conversely, Generation Y may not value this marginal benefit as highly.

H3: In the use of new retail e-commerce assistants, instant retail and self-checkout systems, perceived health benefits of the technologies affect people's judgments of the perceived usefulness of their technologies.

2.8.4 Resistance Factor: Digital Equipment

2.8.4.1 Conception

Digital Equipment (DE) generally refers to devices that can send and receive information via the Internet. This study specifically pertains to portable mobile devices and non-portable devices capable of supporting all behaviours of electronic retail, such as smartphones, tablets, smartwatches, and computers (Editor, 2017).

2.8.4.2 Applicability Of Variable

According to data from the Pew Research Center (2020), the number of smartphone users in China is approximately 911.92 million, making up 63.4% and ranking eighth globally. There are fewer smartphone users among the elderly in China, with only 43.2% of the population over 60 using smartphones (SOHU, 2022). Consequently, few users in China can access new retail, and restrictions on consumer use of digital devices are evident. People cannot complete electronic retail operations in new retail without using digital devices.

2.8.4.3 Hypotheses development

The study contends that personal digital devices fundamentally influence consumers' perceived barriers to adopting retail technology. Based on the Unified Theory of Acceptance and Use of Technology (UTAUT) proposed by Venkatesh et al. (2003), its central construct, facilitation—referring to the objective resources that support technology use—clarifies this relationship. When consumers lack compatible personal devices, they face stronger operational and psychological barriers to retail innovations such as e-commerce assistants, instant retail platforms, and self-checkout systems, including perceived complexity, lack of self-efficacy, or concerns about compatibility.

The study defined personal digital devices as user-owned tools, such as smartphones and tablets, and viewed barriers as multidimensional constraints measured by Likert scales, including complexity, effort expectations, and compatibility issues (Venkatesh et al., 2012). The main difference is that this study emphasises individual technology readiness and clearly separates it from the conveniences offered by supermarkets (such as in-store terminals or employee support). Quantitative validation will employ structural equation modelling (SEM) to examine this negative relationship while accounting for moderating variables like age, digital literacy, and previous experience—factors that have been found to significantly influence technology adoption barriers (Nistor et al., 2019). This definition clarifies the resistance mechanism caused by user-side technological inequality within the technology-enabled retail environment.

H4: Digital equipment impact people's perceived barriers to using new retail technologies, such as new retail e-commerce assistants, instant retail, and self-checkout systems.

2.8.5 Resistance Factor: Perceived Financial Cost

2.8.5.1 Conception

Perceived Financial Cost (PFC) includes all expenses related to using mobile devices, such as smartphones, Internet charges, e-retail platform service fees, product price increases in e-retail, and last-mile delivery costs for products (Tan et al., 2010).

2.8.5.2 Applicability of Variable

The anticipated financial cost is a key barrier to adopting e-services. Luarn and Lin (2015) found that perceived financial costs influence people's intention to use e-commerce. While mobile phone, service, communication, and subscription costs are not present in non-e-commerce fields, these new expenses impact consumers' use of services (Wang et al., 2016).

2.8.5.3 Hypotheses development

The fundamental distinction between new retail and traditional e-commerce is that it internalises product logistics costs; these hidden expenses in physical retail channels are transformed into asymmetric cost exposure faced by consumers (Poon, 2018). Financial costs are not just simple additive expenses, but also cognitive enhancers that increase perceived complexity (Davis, 1989) and compatibility concerns (Rogers, 2003). The elderly group confirms this causal mechanism; the increased data overhead for a single transaction raises the relative cost perception, thereby reinforcing behavioural resistance (Venkatesh et al., 2012).

This structural shift makes logistics costs a source of transaction friction. Empirical research has confirmed that it reduces willingness to adopt technology by increasing

perceived costs (Zeithaml, 1988), which is especially important for price-sensitive groups. The elderly group demonstrates this vulnerability clearly, as low-frequency mobility and the use of data-free packages turn the self-service checkout-forced online payment into a regressive cost. Such mandatory digitalisation essentially acts as a tax on low-engagement users, transforming occasional technology use into a form of financial exclusion (van Dijk, 2020).

H5: When using new retail e-commerce assistants, instant retail, and self-checkout systems, the perceived financial cost has impacted people's perceived barriers to using these technologies.

2.8.6 Resistance Factor: Privacy Risk

2.8.6.1 Conception

Privacy risk (PR) refers to individuals' perceived danger of personal information leakage when using technology (Lim, 2022). In this study, privacy risk indicates how much consumers believe that various supermarket service technologies collect their personal data, such as the coincidence between product recommendations on the supermarket app and items discussed with friends on the same day. It also covers the consistency between product recommendations on the supermarket app and users' search history on other shopping platforms, as well as the alignment between app recommendations and products stored in the user's phone gallery.

2.8.6.2 Applicability of Variable

When a user uses a mobile phone, some APPs exhibit behaviours that compromise consumer privacy, including but not limited to identifying search content, browsing

content, voice calls, household head information, and more (Lee et al., 2019). Software based on the IOS or Android system should inform consumers about all actions of the software in use and non-use states (Zhou et al., 2011). The software should allow users to control the collection of different types of personal information and adjust related settings on their mobile phones after obtaining the user's permission, rather than carrying out activities for any unauthorised purposes (Zhu et al., 2014). Consequently, individuals may experience both benevolent and malevolent privacy infringements when using the supermarket app.

2.8.6.3 Hypotheses development

In the context of the rapid growth of the Internet of Things, the theft of consumer information by smart devices is no longer an isolated incident but has developed into a systemic data exploitation framework (Zuboff, 2019). Corporate practices of personalising and delivering services based on behavioural data are essentially an extension of surveillance capitalism. Valente et al. (2019) revealed that the true nature of data collection is often concealed under the guise of personalised services. This mechanism has led to the Privacy Paradox, where 40% of consumers are explicitly concerned about the privacy threats posed by big data and AI, yet they continue to relinquish rights to technology platforms through their behaviour. Notably, when technological intrusion moves from online environments to physical spaces such as supermarkets, the visibility of privacy infringements is markedly increased (Nissenbaum, 2009), which contributes to the elderly's resistance to technological adoption.

Generation Y may perceive technological privacy risks differently from the elderly, which in turn influences their views on technological barriers. For instance, low digital

literacy hampers their understanding of data flow processes (Hargittai, 2002). This can lead to transforming the mysterious nature of technology into an abstract source of fear. The compulsory use of self-checkout systems results in a loss of control (Bandura, 2001), intensifying the sense of being monitored. Technological interventions in physical spaces disrupt traditional notions of privacy boundaries (Nissenbaum, 2004), with scanning devices seen as physical surveillance tools. This difference in perception shifts privacy threats from potential costs to rigid barriers that inhibit behaviour, a phenomenon that is more pronounced in older groups (Smith et al., 2020).

H6: When new retail e-commerce assistants, instant retail, and self-checkout systems are used, privacy risks impact people's perceived barriers to using these technologies.

2.8.7 Resistance Factor: Perceived Self-Efficacy

2.8.7.1 Conception

Perceived Self-efficacy (PS) refers to individuals' perceptions of their ability to use the target technology, indicating how much they believe they can successfully carry out such operations (Karen, 2011). In the health study by Schneider (2016), self-efficacy is the confidence of patients to act in their healthcare. Furthermore, self-efficacy affects the ability to overcome obstacles or difficulties when using a technological innovation (Bandura, 2002). In this study, self-efficacy relates to whether individuals can use various technologies provided by supermarkets, such as human-computer interaction technology, self-checkout technology, and online real-time retail technology.

2.8.7.2 Applicability of variable

To identify factors influencing technology adoption, the effects of self-efficacy and facilitating conditions have been examined (Bhattacherjee et al., 2008). The study by Taipjutorus et al. (2012) explored how self-efficacy impacts the adoption rate in e-learning systems. Additionally, few studies have demonstrated that self-efficacy significantly affects a user's attitude (Őzokcu, 2018).

Mobile self-efficacy indicates confidence in using mobile devices to achieve desired goals (Mark et al., 2011). Additionally, mobile self-efficacy becomes a crucial factor influencing consumer behaviour towards adopting mobile-related technology. Many researchers have explored the impact of mobile self-efficacy on mobile-based adoption of technology, including mobile data services (Yang, 2010), mobile health services (Sun et al., 2013), and mobile banking services (Khraim et al., 2011). Therefore, Suls and Wallston (2008) stated that users' self-efficacy is vital in motivating them to adopt new technology.

2.8.7.3 Hypotheses development

According to Cruz-Cárdenas et al. (2021), during the COVID-19 outbreak, five factors influenced consumer behaviour amidst the Pandemic: technical, sociocultural, political-legal, and financial contexts. Prior studies by Baicu et al. (2020) and Sheth (2020) identified that COVID-19 and available technologies encourage consumers to adopt technological innovations for their consumption. Conversely, Fiestas and Tuzovic (2021) indicated that retailers have recently addressed the integration of online and offline channels to assist consumers in cross-channel shopping via web rooming and showrooming. iVend Retail (2021) reported that 83.8% of consumers engaged in showrooms, while 91.4% purchased through webroom. Previous studies

(Schneider & Zielke, 2020; Fiestas & Tuzovic, 2021) identified that mobile devices enable consumers to engage in integrated channels.

Similarly, Juaneda-Ayensa et al. (2016) and Verhoef et al. (2015) reported that smartphones are essential in guiding consumers to achieve a seamless shopping experience across omnichannel platforms. Indirectly, mobile devices provide platforms for consumers to engage in webrooming and showrooming, combining online and offline channels (Goraya et al., 2020). Therefore, consumers' mobile self-efficacy affects their intention to adopt new retail approaches when making purchases. For instance, consumers with high mobile self-efficacy can use smartphones to scan QR codes or barcodes with mobile apps to access product information and prices in both online and physical stores (Daurer et al., 2015).

Furthermore, Perry et al. (2019) confirmed that mobile technologies expand retail sales in physical stores by increasing the customer base through online channels, since mobile devices are comparable to computers with unrestricted internet access. As a key factor in integrating both online and offline channels to enable cross-over shopping for consumers, mobile devices allow users to access the internet anytime and anywhere to shop (Santos & Gonçalves, 2019).

In addition, a combination of geo-localisation (GPS) technologies and mobile device technologies supports consumers in shopping locally and encourages showrooming among consumers (Viejo-Fernández et al., 2020). Self-efficacy is an effective predictor of consumers' adoption of new technology, since acceptance of particular information systems is impacted by self-efficacy (Gbongli et al., 2019). During the outbreak of COVID-19, self-efficacy acted as a critical factor in predicting health-

related behaviour adoption and mobile payment adoption (Sreelakshmi & Prathap, 2020). Moreover, mobile banking adoption among consumers is significantly influenced by their mobile self-efficacy (Foroughi et al., 2019).

Additionally, numerous studies have confirmed that consumers' self-efficacy significantly affects their consumption behaviour, whether offline or online (Hansen, 2008; Cho et al., 2018; Wang et al., 2020). Several relevant pieces of literature also found that self-efficacy significantly influences satisfaction (Karim et al., 2020), use intention (Daragmeh et al., 2021; Rodr ǵuez-Priego & Porcu, 2021), and actual use (Kim & Kim, 2020).

H7: When using new retail e-commerce assistants, instant retail, and self-checkout systems, perceived self-efficacy impacts people's perceived barriers to using these technologies.

2.8.8 Resistance Factor: Perceived Barriers

Perceived barriers (PB) refer to obstacles to behavioural change or involvement in technological innovation, such as cost, inconvenience, and discomfort (Al-Dmour et al., 2020). In the field of new retail technology, perceived barriers refer to the obstacles faced by elderly individuals when using instant retail, e-commerce assistants, and self-checkout terminals.

2.8.8.1 Conception

PB prevented necessary health measures for breast cancer screening (Mohamed et al. 2015). During COVID-19 in Pakistan, overcrowding in emergency rooms was one of the barriers to infection control of COVID-19 (Saqlain et al., 2020). Thus, the negative

effects caused by PB could disrupt people's attitudes or behaviours (Al-Tahitah et al, 2021). Previous studies employed perceived benefits and perceived barriers as independent variables. During the COVID-19 outbreak, the perceived benefits of consumers significantly influenced the adoption of preventive behaviours towards COVID-19, while there was an insignificant relationship between PB and the adoption of preventive behaviours (Kim & Kim, 2020).

2.8.8.2 Applicability of Variable

PB recommends improving preventive strategies due to the very high risk of the Pandemic (Kim & Kim, 2020). For example, supermarkets have introduced manual recording service centres for elderly people who do not have smartphones, rather than relying on trip tracking based on QR code scanning. Similarly, Jose et al. (2020) also evaluate the effects of perceived benefits and perceived barriers towards protective behaviour during the Pandemic. They found a significant positive effect of perceived barriers on adopting protective actions during the pandemic, as various channels provided conflicting information about it. Additionally, perceived benefits and perceived barriers among consumers have shown a significant effect on visit intentions (Ban & Kim, 2020) and the intention to use contact tracing apps (Walrave et al., 2020) during the Pandemic.

2.8.8.3 Hypotheses development

When using new retail technologies, the obstacles faced by the elderly are not isolated but form a five-dimensional structure. These five obstacles include: first, the device gap, which refers to the lack of contact with technology due to the absence of smart terminal devices (van Dijk, 2005); second, the efficacy deficit, meaning low self-

efficacy among individuals, making it difficult to feel in control or adapt (Bandura, 1997); third, financial sensitivity, where high or uncertain costs of technology use trigger the individual's loss aversion mechanism (Kahneman & Tversky, 1979); fourth, privacy vigilance, as concerns over personal data being misused increase, leading the elderly to adopt a more defensive attitude (Smith et al., 2020); and fifth, the technology tax, which refers to the cognitive burden created by complex operations and constantly updated systems, resulting in additional psychological costs (Sweller, 2011). Collectively, these five barriers form a complex vulnerability structure that causes the perceived barriers to new technology among elderly users to multiply across multiple dimensions (Chen & Chan, 2014), far beyond what can be explained by the linear logic of the traditional technology acceptance model (TAM).

Based on the above mechanism, perceived barriers not only represent individuals' rejection of technology but also trigger a value dissolution effect. In the perception process, the perceived usefulness of technology is no longer solely derived from its convenience but is reconstructed through the combined effects of barrier intensity and vulnerability index. This means that individuals' judgment of the value of technology shifts into a cost-benefit imbalance function. Behavioural intention manifests as a threshold breakthrough mechanism: only when perceived benefits significantly exceed the barrier threshold borne by the individual can behavioural intention be activated (Venkatesh et al., 2012). Taking the elderly's perception of self-checkout systems as an example, they are often viewed as a combination of three burdens (financial expenditure, learning cost, and privacy exposure), which leads to a systematic underestimation of the benefits of technology (Li et al., 2020), ultimately resulting in the erosion of individual agency — that is, technology is no longer seen as an empowering tool but has become a symbol of oppression (Sellen et al., 2009).

Furthermore, neurodecision-making research offers a biological foundation for this model: multiple obstacles can cause cognitive overload in the prefrontal cortex, hindering the individual's capacity to assess long-term interests; financial risks and privacy concerns will activate the threat detection system of the amygdala, leading the individual to focus on avoiding potential losses; and the signal inhibition phenomenon of the nucleus accumbens, part of the reward centre, suggests that the neural response to the potential benefits of technology will be drowned out by the noise of obstacles (Telpaz et al., 2015). Together, these three neural mechanisms produce an Intention Freezing Effect.

H8: In using new retail e-commerce assistants, instant retail and self-checkout systems, perceived barriers impact people's perceived usefulness to using new retail technologies.

H9: In using new retail e-commerce assistants, instant retail and self-checkout systems, perceived barriers impact people's intention to use new retail technologies.

2.8.9 Group Factors: Movement Restrictions

2.8.9.1 Conception

Movement restrictions (MR) generally refer to individuals' physical limitations when trying to engage in certain behaviours (Morrison et al., 2021). In this study, movement restrictions relate to the constraints on Generation Y caused by work and lifestyle commitments, leaving them with limited time to visit supermarkets. It also covers elderly individuals who are physically restricted from visiting supermarkets due to limitations in their physical abilities, such as shaky hands that prevent them from

completing self-checkout tasks like scanning items and making self-payments through scanning codes.

2.8.9.2 Applicability of Variable

Situational strengths generally refer to individuals responding suitably to their circumstances. This means that situational strength can either promote or obstruct behaviour by exerting pressures on people (Meyer et al., 2014). Young people in digital society do not need to exert effort to accept mobile payments. It has become an inherent part of their lives to use digital technology from birth.

In China, Gen Y's movement restrictions suggest they may lack the time and energy for supermarket shopping. They often bear responsibilities such as caring for children and elders and completing heavy tasks assigned by their organisation (Hassan et al., 2023). It is uncertain whether this heavy pressure prevents them from engaging in face-to-face shopping and leads them to opt for instant retail. Compared to younger individuals, older people's physical limitations restrict their mobility, and many are unable to participate in traditional offline shopping.

2.8.9.3 Hypotheses development

Lw News (2022) states that elderly individuals in China face mobility challenges and find it difficult to complete tasks related to travel and shopping independently. Online retail within the new retail industry offers a shopping channel that caters to their needs without requiring them to leave their homes. Meanwhile, transportation remains another concern for the elderly. While young people can drive, use taxis, or rely on public transportation, older individuals often lack driving skills, and the problem of taxi refusal is common. Sun and Hu (2022) note that elderly Chinese people encounter

difficulties accessing taxi services, as drivers are concerned about their health and frequently refuse to pick them up.

Additionally, with the widespread adoption of digital technology, older people face more digital barriers, such as ride-hailing platforms or scanning codes for mall entry (Xinhua, 2020). It has not been reported whether these factors contribute to an increased willingness among elderly Chinese individuals to use online retail within the new retail industry. The Situational Strength Theory helps to explain how older adults' decision-making and behaviour are influenced by the constraints imposed by their physical mobility limitations.

H10: Movement restrictions impact people's intention to use new retail technologies such as e-commerce assistants, instant retail, and self-checkout systems.

2.8.10 Group Factors: Social Influence

2.8.10.1 Conception

Social influence (SR) broadly refers to the extent to which individuals are persuaded by encouragement from family and friends and their desire to change or reinforce their opinions (Joa & Magsamen-Conrad, 2022). In this study, social influence refers to the effect on elderly individuals from other seniors or their children regarding supermarket digital technology.

2.8.10.2 Applicability of Variable

SR is vital in assessing consumer technology acceptance (Karahanna & Limayem, 2000). In this study, social influence encompasses individuals important to consumers, such as social media and social networks. Alexa et al. (2021) mentioned that social

influence is a factor affecting consumers' beliefs. Consumers' intentions are closely linked to their key people, like family and friends. Furthermore, Goodwin et al. (2009) proposed that discussions with family and friends can impact a person's concerns. Therefore, family and friends are significant factors shaping an individual's behaviour or actions (Prati et al., 2010).

During the outbreak of COVID-19, Dryhurst et al. (2020) stated that social networks and information obtained from friends and family influence the public's risk perception. Therefore, social media plays a crucial role in predicting the adoption of protective behaviour (Ning et al., 2020). Along with the relevant literature, social media influence demonstrated a significant effect on consumers' online purchase intentions (Doan, 2020) and COVID-19 preventive behaviour (Kim & Kim, 2020).

Along with the relevant literature (Chong et al., 2012; Tsu Wei et al., 2009; Blaise et al., 2018; Noraah Mohd, 2013), social influence remains the primary factor in examining the intention to use mobile commerce. New retail innovation involves the integration of both online and offline channels in the retail industry, with mobile devices identified as a key driver.

Blaise et al. (2018) suggested that mobile devices are very sensitive when interacting with friends and family because their use can interrupt social gatherings. Therefore, opinions from important people indirectly influence the adoption of new retail techniques in the shopping process. Furthermore, decisions or reviews from previous users also affect beliefs and personal decision-making (Norazah Mohd, 2013). Additionally, Lu (2014) demonstrated that interaction within digital social networks significantly impacts smartphone adoption. Similarly, interaction in digital social

networks is likely to influence the adoption of new retail, as users share their reviews online. Earlier scholars (Pookulangara et al., 2011; Rejón-Guardia & Luna-Nevarez, 2017) reported that social influence affects consumers' behavioural intentions towards showrooming. As previously mentioned, showrooming and webrooming are identified as mechanisms of new retail, so social influence may serve as a variable for predicting consumers' intentions towards new retail within the shopping process.

2.8.10.3 Hypotheses development

Although traditional technology acceptance models have widely confirmed the positive effect of social influence (SI) on usage intention (Koch et al., 2020; Troise et al., 2021), this study found that in the post-epidemic era, SI exhibited a structural weakening or even a reverse trend among the elderly. This phenomenon reflects the applicability limits of the classic UTAUT model in the face of social crises and high-risk perception situations. The study further introduced social neurodynamics and crisis situation compensation theory, revealing that SI is not a stable, unidirectional promoting variable, but a dynamic regulatory factor deeply linked with the neural trust processing system (Liu et al., 2021; Barnes et al., 2021). Particularly during the peak of the epidemic, supermarket new retail technology was attributed with digital epidemic prevention, which enabled social influence to activate the mirror neuron system and significantly increase the adoption rate of apps among the elderly (Koch et al., 2020). However, after the epidemic stabilised, the technology rejection sentiment among the elderly sharply increased (Troise et al., 2021). Data show that in 2023, the proportion of elderly people in urban Shanghai using supermarket apps fell from 92% at its peak to 67%, and this core mechanism can be attributed to trust conflict neural responses triggered by social influence.

To overcome the explanatory bottleneck of traditional SI theory, this study reconstructs the mechanism of social influence on the elderly's intention to use. The model indicates that the key to converting social influence into behavioural intention is whether it can positively motivate actual behavioural intention. Two reactions, compliance abandonment or anxious escape, may cause the elderly to withdraw from the social circle of new retail use (Cambridge Geriatric Neuroscience Laboratory, 2024). Three social information interference factors, intergenerational conflict, media anxiety, and peer negativity, significantly hinder technology adoption intention. Corresponding measures include introducing public security anti-fraud certification logos and displaying successful peer cases through AR visualisation to create a positive neural reference loop and establish a multidimensional trust anchor system (Liu et al., 2021; Barnes et al., 2021). In this context, this study focuses on how social factors influence consumers and whether they increase their willingness to use new retail technologies.

H11: In using new retail e-commerce assistants, instant retail and self-checkout systems, social influence impacts people's intention to use new retail technologies.

2.8.11 Group Factors: Perceived Usefulness

2.8.11.1 Conception

Perceived usefulness (PU) generally refers to individuals' perceptions of how technology enhances efficiency or outcomes in specific areas (Cebeci et al., 2020). In this study, perceived usefulness specifically relates to people's perceptions of the value of supermarket self-checkout technology, instant retail technology, and e-commerce assistants.

2.8.11.2 Applicability of Variable

Since new retail innovation offers services for product purchase, returns, and exchanges through online or physical stores (Shi et al., 2020), it improves consumer convenience for daily shopping. Fevad (2017) showed that French consumers prefer buying via integrated channels rather than solely through physical or online stores after experiencing different shopping methods. Additionally, Asian consumers favour using new retail innovations to obtain goods (Zhu et al., 2018).

Therefore, new retail innovations assist retailers in reaching more potential customers and retaining existing customer bases (Gensler et al., 2017). Combining online and offline channels creates a better environment and services by synchronising information across both channels, such as store location, business hours of physical stores, discount and promotional details, and product assortment structure (Garaya et al., 2020). Such perceived benefits improve consumers' intention to integrate both online and offline channels.

Consumers are concerned about comparing prices and products, which leads them to engage in a webroom, where they browse items online and then make purchases in-store. Conversely, quality- and appearance-sensitive consumers prefer to examine products in-store, allowing them to touch and try them before immediately collecting their purchase. Therefore, an integrated shopping channel framework in the retail sector enables consumers to make purchases with cross-channel free-riding behaviour (Arora & Sahney, 2018). Additionally, prior studies (Garaya et al., 2020; Zhu et al., 2018) confirm that the convenience of shopping encourages consumers' behavioural intention to adopt a shopping channel. The conveniences of shopping include saving

time, easy price comparison, convenient goods delivery, and high accessibility, which can be accessed at any time and from any location.

2.8.11.3 Hypotheses development

In the traditional acceptance model of information systems, perceived usefulness (PU) is generally seen as a key factor influencing the intention to use (Al-Maghrabi et al., 2011). Specifically, in the context of mobile shopping and instant retail technology, studies have demonstrated that PU significantly boosts users' willingness to adopt the technology (Doan, 2020; Yang & Farney, 2013). However, when it comes to the elderly, the core dimensions that PU depends on - such as time efficiency, ease of use, and shopping effectiveness (Kleijinen et al., 2007) - have not effectively engaged the neural mechanisms directly linked to the formation of intention in real cognitive processing.

Kramer et al. (2022) empirically demonstrated through fMRI that traditional PU activates the reward pathway in young people, leading to dopamine release, while in the elderly group, it more frequently activates the anxiety response area of the anterior insula. This neural response difference reveals the PU misalignment effect, meaning that the same technological features that serve as a reward for young people may be perceived as potential risks by the elderly, thereby reducing their intention to use. According to previous research, PU has a significant influence on consumers' adoption of mobile or instant retail (Doan, 2020; Yang & Farney, 2013) and their intention to use online or mobile banking (Foroughi et al., 2019; Rahi et al., 2020; Rahi & Ghani, 2019). Consequently, this study aims to clarify how perceived usefulness impacts consumers' intentions to use supermarket technology.

To clarify the nonlinear relationship between PU and intention in the elderly group, this paper argues that the elderly are less likely to see PU as an improvement in instrumental efficiency during technology use and are more inclined to make risk-rebalancing judgments. Specifically, in the elderly's PU evaluation mechanism, the weights of survival security and operational safety play a significant role in forming their final utility assessment. This finding suggests that the core of elderly PU lies in whether their nervous system can interpret the technology's function as enhancing life stability rather than just abstract efficiency indicators like time savings. Accordingly, there is a substantial difference between the perceived usefulness in this study and conventional notions of usefulness. The researchers boldly speculate that perceived usefulness among the elderly relates to their willingness to use, whereas the willingness among Generation Y is influenced not by health content or obstacles but by the traditional perceived usefulness of technology.

H12: In the use of new retail e-commerce assistants, instant retail and self-checkout systems, perceived usefulness impacts people's intention to use new retail technologies.

2.8.12 Social Factor: Facilitating Conditions

2.8.12.1 Conception

Facilitating conditions (FC) are the environmental supports individuals encounter when using specific technologies, such as reliable internet access or businesses providing devices related to the technology (Wang et al., 2020). In this study, facilitating conditions refer to supermarket self-checkout terminals, instant retail apps, e-commerce assistant systems, and internet signals.

2.8.12.2 Applicability of Variable

For example, the conditions of smartphones, network coverage, features, and the availability of mobile apps influence consumers' intention to shop through new retail channels. Furthermore, social distancing policies and regional lockdowns have encouraged the adoption of technology-mediated purchase methods (Butu et al., 2020). Zawanka and Buff (2020) reported that purchasing through online channels has become a strong trend among populations.

Hence, many relevant studies indicate that consumers prefer to buy goods through online channels (Antoides and van Leeuwen, 2020; Hassen et al., 2020; Wang et al., 2020). Additionally, the frequency of purchases in physical stores also decreased (Laguna et al., 2020; Wang et al., 2020). Li et al. (2020) also suggested that consumers favour daily purchases from small local retailers rather than large retailers.

Cruz-Cárdenas et al. (2021) reported that the pandemic encouraged people to learn about technological innovation to access and use new technologies. The implementation of technological innovation helps people carry out their daily activities while still adhering to regional lockdowns and social distancing policies. For example, mobile devices or computers with internet access allow consumers to purchase their daily essentials without visiting physical stores. They also check the needed products in-store and buy them online to avoid queues and reduce physical contact and crowding. Therefore, facilitating conditions influence personal decisions to adopt new retail methods during the pandemic.

To boost the adoption of new retail concepts, enabling conditions should be improved to bridge the technology implementation gaps across different societal levels. For

instance, access to technology-based services remains limited among older and low-income populations (Cruz-Cárdenas et al., 2019). Additionally, understanding technology applications and digital devices is essential to motivate consumers to adopt new retail practices during their daily shopping (Cruz-Cárdenas et al., 2021; Parasuraman & Colby, 2015).

2.8.12.3 Hypotheses development

Some previous studies (Saghiri et al., 2017) identified facilitating conditions, such as Omni-channel, which provide an environment for consumers to choose from various characteristic products and encourage them to shop across integrated channels. Garaya et al. (2020) reported that assisting services from integrated channels enhance consumers' shopping intentions through these channels. Similarly, Emrich et al. (2015) and Zhang et al. (2018) demonstrated that retailers using integrated channels help to fulfil consumer requirements and support them in the goods delivery and payment processes during purchase.

Conversely, webrooming and showrooming are common behaviours among consumers that facilitate the adoption of integrated channels. Therefore, an integrated shopping store is necessary to encourage consumer engagement and promote cross-channel shopping behaviour (Zhu et al., 2018). Responsive services across retailers' integrated channels provide consumers with a high-quality purchasing experience both online and offline. Consequently, Zhu et al. (2018) proposed that servicing retailers with integrated channels increases consumers' satisfaction and confidence in these channels. Based on the findings of these scholars, enabling conditions that foster or encourage consumer intention to shop through new retail platforms include services, assistance, and accessibility via online and offline channels. High-quality facilitating

conditions offered by retailers indirectly boost consumers' intention and confidence towards channel integration (Garaya et al., 2020).

Several researchers have used facilitating conditions to study consumer acceptance of technology. In this study, facilitating conditions refer to a technological environment that helps consumers use new retail innovations. Therefore, enabling conditions may be vital in encouraging people to adopt new retail options. Consumers' intention to use restaurant mobile apps to order meals was significantly influenced by facilitating conditions (Palau-Saumell et al., 2019). Similarly, Doan (2020) found that facilitating conditions greatly affect consumers' intention to purchase online. Additionally, within the educational context, facilitating conditions positively influenced the adoption of online learning platforms (Rita et al., 2020) and shaped students' attitudes towards educational telepresence robots (Hon & Conti, 2020). In this regard, this study suggests that facilitating conditions impact the decision-making of both elderly individuals and Generation Y regarding the use of new retail technologies.

H13: New retail e-commerce assistants, instant retail, and self-checkout systems create conditions that influence people's adoption of new retail technologies.

2.8.13 Usage Factors: Intention To Use and Using Behaviour

2.8.13.1 Conception

Intention to use (ITU) refers to the extent to which individuals want to use a particular technology at a specific time, including future use. Usage behaviour (UB) broadly describes past and current use of technology (Abu-Taieh et al., 2022). In this study, usage intention and behaviour concerning the use of e-commerce assistants, instant retail, and self-checkout technologies by elderly individuals and Generation Y.

2.8.13.2 Applicability of Variable

Numerous previous studies have identified factors that influence people's decision-making. Age is a common topic for studying consumer behaviour. However, previous research has yielded inconsistent results. Cruz-Cárdenas et al. (2021) suggested that this inconsistency could be due to local cultural issues and research methodology factors, such as questionnaires that produce conflicting results. These prior studies focus on different products.

Lins and Aquino (2020) carried out a study on the general product, Wang et al. (2020) focused on food products, while Dammeyer (2020) questioned respondents about food, medicine, and hygiene products. Unfortunately, the same result also appears in the age factor. Dammeyer (2020) reported that age did not influence consumers' purchase behaviour, whereas Lin and Aquino (2020) stated a negative relationship between age and purchase behaviour.

Behavioural intention is the primary factor influencing the use of a specific system or concept (Venkatesh et al., 2002). Some relevant literature (Papau-Saumell et al., 2019; Rodríguez-Priego & Porcu, 2021) reported that consumers' intention to use significantly affected the actual adoption of a system. This indicates that elderly individuals may be negatively impacted by age-related factors, leading to reluctance in using supermarket technology.

2.8.13.3 Hypotheses development

In the study of new retail technology adoption behaviour among the elderly, there is a notable decoupling phenomenon between intention and actual use. Although Tao (2009) pointed out that there is no significant correlation between intention and actual

use, and attributed this to subjective reporting data bias, this conclusion is more pronounced in the elderly population. Neuroscience research indicates that the efficiency of neural conduction between the prefrontal cortex and the primary motor cortex in the elderly is significantly reduced, leading to a disconnect between intention formation and behaviour execution.

Especially when faced with rapidly changing supermarket situations, the elderly's ability to adapt to the environment is greatly diminished due to the decline in the hippocampus's contextual memory function, which further worsens the occurrence of the Intention-Behaviour Chasm (IBC). When the IBC index (calculated by the ratio of prefrontal theta wave power to motor cortex μ rhythm synchronization, multiplied by the environmental interference factor) surpasses 0.82, the likelihood of the elderly actually initiating behaviour decreases sharply (MIT AgeLab, 2023).

However, actual behaviour generation is not driven by intention alone but by the synergistic effect of a series of neural gating mechanisms. The continuous use model proposed by Lin (2011) shows a triple gating structure in the elderly group: first, cognitive gating is regulated by the anterior cingulate gyrus, which determines whether the behaviour meets the necessity of survival. Simulating crisis scenarios such as epidemics can activate related memory channels to enhance conversion rates; second, emotional gating is regulated by the insular cortex, and negative experiences (such as complex interfaces or failed checkouts) will be quickly suppressed, while pleasant feedback (such as the sound effect of successful checkout) will help the internalisation of continuous behaviour; finally, motor gating is responsible for the basal ganglia, and new behaviours need to be repeatedly trained to form procedural memory before they can be preserved for a long time (Seidler et al., 2010).

After fixed operation path training, elderly trainees developed stable muscle memory and increased their self-service checkout completion rate, which clearly demonstrates the trainability of behaviour solidification. Some studies unrelated to the elderly have shown that use intention also significantly influences actual consumer behaviour (Mohammadi, 2015). This suggests that the behaviour of Generation Y may be affected by intention, whereas the relationship between use intention and behaviour in the elderly may be invalid unless they have undergone extensive training, requiring ongoing assistance or supportive learning policies from society.

H14: In using new retail e-commerce assistants, instant retail and self-checkout systems, intention to use impacts people's using behaviour of new retail technologies.

2.8.14 Experience

2.8.14.1 Conception

Experience refers to individuals' knowledge or understanding of certain things, which may result from learning, observation, or personal encounters (Kim, 2021). In this study, experience pertains to whether individuals have used these new retail-related technologies during the pandemic or earlier.

2.8.14.2 Applicability of Variable

Experience allows individuals to make better-informed responses and decisions in specific settings, often resulting in appropriate actions that help them solve problems swiftly and accurately. Blackwell et al. (2014) found that experienced practitioners are more likely to utilise digital technologies and seek their advantages more often.

Hills and Thomas (2020) suggest that experiential engagement with digital technology leads to a deeper understanding of its advantages and limitations. In the case of older adults, their lack of experience with digital technology may result in reluctance or abandonment of its use. An interesting phenomenon is the widespread adoption of mobile payments in developing countries. For example, Malaysia experienced a surge in mobile payment usage during the pandemic, and even after the pandemic, people continued to embrace this technology, recognising the benefits it brings to their lives.

2.8.14.3 Hypotheses development

With the outbreak of the COVID-19 pandemic, China's elderly population has seen an unprecedented surge in the use of digital technology. According to Alibaba's Silver Generation Digital Life Report cited by the Yangtze Evening News (Yangtse, 2020), the number of elderly internet users in China increased by 27.9% during the pandemic, and the order volume on new retail platforms such as Hema even surpassed that of the post-90s and post-00s. This phenomenon is not coincidental, but a systematic overcoming of technical barriers driven by survival needs in crisis situations. In the context of restrictions on traditional shopping methods, the elderly have come to see new retail platforms as essential tools to maintain their daily lives, rather than optional alternatives. This shift also confirms Venkatesh et al.'s (2020) theoretical expectation that extreme circumstances reshape the logic of technology adoption.

Neurocognitive research further reveals that the decision-making behaviour of the elderly in crisis situations exhibits the phenomenon of basal ganglia suppressing the function of the prefrontal cortex, which means the immediate benefit signal triggered by the survival instinct has an inhibitory effect on the risk assessment mechanism within the nervous system, thereby promoting short-term behavioural responses (Hsu

et al., 2022). Simultaneously, the theory of brain neuroplasticity demonstrates that high-frequency digital behaviour practices, passively initiated during the epidemic, can assist the elderly brain in establishing new technological processing pathways within a 6-8 week period, enabling passive development of digital skills.

In the post-epidemic phase, this crisis-driven behaviour adoption has not diminished but has achieved long-term entrenchment of behavioural stickiness through a dual-path mechanism. The first pathway involves the habit neural solidification mechanism: prolonged use of new retail technology shifts the operation process from conscious control by the prefrontal lobe to automatic processing by the basal ganglia, thereby reducing behavioural costs and cementing behavioural habits (Wood & Rünger, 2016). The second pathway is the benefit cognitive reconstruction mechanism: the utility of technology, enhanced during the epidemic, becomes a cognitive schema that continues to influence individuals' long-term judgments of technology's value (Piaget, 1952).

In megacities such as Shanghai, these two pathways are further integrated due to the embedding of institutional environments like community group buying and local instant retail, which encourages the development of a digital tribal behaviour structure among elderly users on social networks (Putnam, 2020). Empirical data also supports the existence of this behaviour lock-in pathway. Electroencephalogram (EEG) research additionally confirmed that when high-frequency users perform related technical tasks, the activation energy consumption in their brain decision-making areas decreases by 62%, indicating that their technology use has entered a stage of neural efficiency improvement (Haier et al., 2018). Research suggests that individuals with experience are more likely to master technology and develop behavioural habits.

H15: Using new retail e-commerce assistants, instant retail, and self-checkout systems impacts people's behaviour regarding new retail technologies.

2.9 Summary of Research Hypothesis

H1: When using new retail e-commerce assistants, instant retail, and self-checkout systems, people's perceived susceptibility to the pandemic affects their perceptions of their technologies' usefulness.

H2: When using new retail e-commerce assistants, instant retail, and self-checkout systems, the perceived severity of the pandemic affects people's judgments of their technologies' usefulness.

H3: When using new retail e-commerce assistants, instant retail, and self-checkout systems, the perceived health benefits of the technologies affect people's perceptions of their usefulness.

H4: Digital equipment must impact people's perceived barriers to using new retail technologies, such as new retail e-commerce assistants, instant retail, and self-checkout systems.

H5: When using new retail e-commerce assistants, instant retail, and self-checkout systems, perceived financial cost impacts people's perceived barriers to using new retail technologies.

H6: Privacy risks impact people's perceived barriers to using new retail technologies, such as e-commerce assistants, instant retail, and self-checkout systems.

H7: When using new retail e-commerce assistants, instant retail, and self-checkout systems, perceived self-efficacy impacts people's perceived barriers to using these technologies.

H8: In using new retail e-commerce assistants, instant retail and self-checkout systems, perceived barriers impact people's perceived usefulness to using new retail technologies.

H9: In using new retail e-commerce assistants, instant retail and self-checkout systems, perceived barriers impact people's intention to use new retail technologies.

H10: Movement restrictions impact people's intention to use new retail technologies such as e-commerce assistants, instant retail, and self-checkout systems.

H11: In using new retail e-commerce assistants, instant retail and self-checkout systems, social influence impacts people's intention to use new retail technologies.

H12: In the use of new retail e-commerce assistants, instant retail and self-checkout systems, perceived usefulness impacts people's intention to use new retail technologies.

H13: New retail e-commerce assistants, instant retail, and self-checkout systems facilitate conditions that impact people's use of new retail technologies.

H14: In using new retail e-commerce assistants, instant retail and self-checkout systems, intention to use impacts people's using behaviour of new retail technologies.

H15: Using new retail e-commerce assistants, instant retail, and self-checkout systems impacts people's behaviour regarding new retail technologies.

H16: Perceived usefulness has a mediating role between perceived barriers and intention to use among Gen Y and Baby Boomers.

2.10 Conceptual Framework

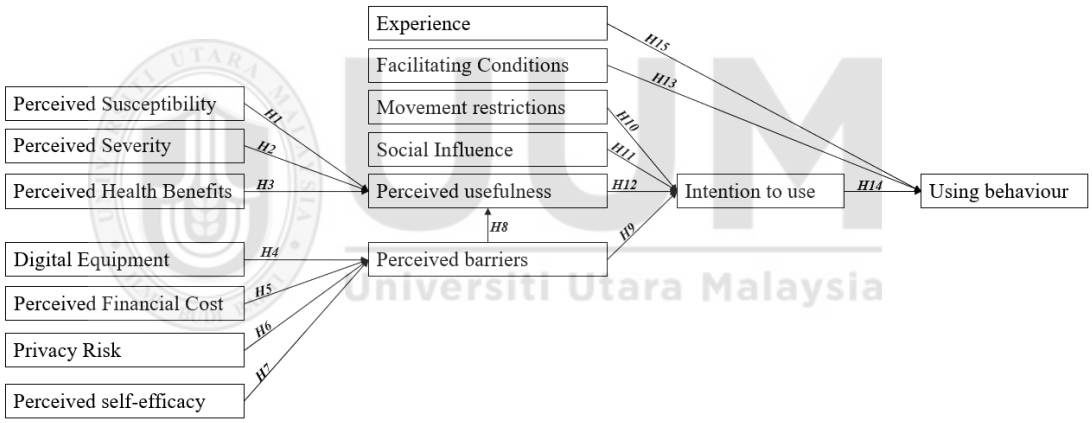


Figure 2.9 Conceptual Framework

2.11 Theoretical Framework Basis

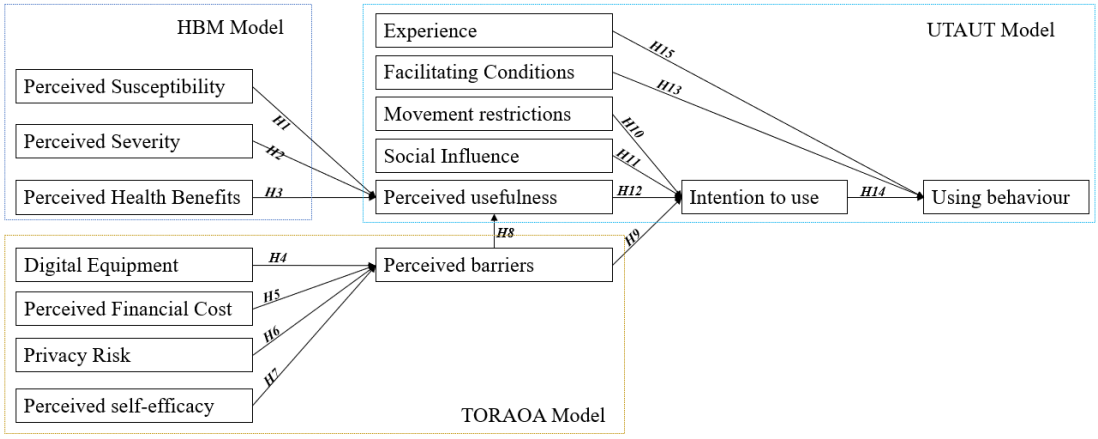


Figure 2.10 Theoretical Framework Basis

2.12 Chapter Summary

The chapter offers a review of relevant literature. All dependent and independent variables are clearly defined by comparing them with previous research. The research model and literature review establish the relationship between these variables. This model facilitates the formulation of a research hypothesis aligned with the research objectives. It is important to note that the study utilised a higher-order model concerning perceived usefulness and perceived barriers. Finally, the methodology applicable to conducting this study is outlined in Chapter 3.

CHAPTER THREE

RESEARCH METHODOLOGY

3.1 Introduction

Chapter three details the research methodology and design used to achieve the study's objectives. It outlines the characteristics of the population and sample, the sampling frame methodology, and the analytical procedures. Additionally, it describes the questionnaire design and data collection methods. The analysis includes descriptive statistics, reliability, and validity tests.

3.2 Research Philosophy

Research philosophy offers support and clues about the inherent laws of research development (Saunders et al., 2009). Therefore, it is important to understand different types of philosophy. Saunders et al. (2009) indicated that positivism, realism, and interpretivism are the main research philosophies. According to Healy and Perry (2000), positivism relates to a single, concrete reality, whereas interpretivism pertains to multiple realities, and realism concerns various perceptions of an independent reality.

3.2.1 Positivist Philosophy

Positivism philosophy relies on relevant literature and prior academic theories to justify research objectives (Bryman & Bell, 2015). Positivist and interpretivist research are established approaches, although somewhat older, especially when compared to realism and pragmatism (Mitev & De Vaujany, 2012). This study adopts a positivist research approach. Positivist research is characterised by a commitment to scientific dominance, emphasising objective observation and description of real phenomena to uncover specific laws (Levin, 1988).

Positivist research generally takes place in areas that have already been explored or is used to test hypotheses within similar fields (Park et al., 2020). Since new retail is not an entirely new idea, a positivist research approach provides a suitable basis. In positivist research, quantitative methods, which adhere to deductive principles, are commonly employed. This approach relies on statistical data analysis, enabling the evaluation of hypotheses and clarifying the different effects that independent variables have on the dependent variable (Yu et al., 2002).

General laws in society often require gathering data on a specific scale, making the data collection process in effective quantitative research worth paying attention to. Sarantakos (2005) suggested that positivism is a highly objectivist perspective; anything that can be perceived through the senses is considered genuine. Within positivism, researchers focus on the theoretical background and exclude external factors during analysis. Furthermore, a large amount of data has been collected for a study (Saunders et al., 2009). Statistical analysis offers criteria for evaluating the conclusions of positivist research.

3.2.2 Deductive Reasoning

The study employed a deductive approach rather than an inductive one. Deductive reasoning involves researchers applying previously established theories and conclusions to evaluate a phenomenon in the present (Johnson-Laird, 1999). In this study, researchers hypothesised about the factors influencing consumers' adoption of new retail behaviours following the pandemic, based on the effects of UTAUT, HBM, TORAOA on consumer behaviour, and formulated 16 hypotheses.

3.2.3 Quantitative Research

This study employed quantitative research. Quantitative methods are used to gather significant data to assess the impact of independent variables on new retail adoption. Public perception and intention were examined through a survey questionnaire to support the research objective and hypothesis. Primary data was collected and analysed to meet the research objectives. Quantitative research is more effective at describing certain broad societal phenomena (Watson, 2015). Data can also be used to intuitively identify the factors influencing specific social phenomena (Bloomfield & Fisher, 2019).

Based on the research purpose, the quantitative method is used as a research measure to achieve the goals of this study. Johnson and Turner (2003) described the quantitative method as an objective measure, with data collected through surveys and analysed using statistical, mathematical, or numerical procedures. Additionally, the quantitative method is employed to investigate a phenomenon using numerical data collection across a targeted group (Babbie, 2010). This study utilises statistical methods to identify relationships between different variables.

3.2.4 Primary Data

This study used primary data collection methods instead of secondary data from other individuals or organisations. Primary data is fresh, original, authentic, and highly adaptable (Hox & Boeije, 2005; Ajayi, 2017). In this study's context, relevant secondary data was limited and difficult to find in various data repositories in China. Due to the lack of existing data and the limitations of secondary data, primary data was selected as the only data source for this research.

3.3 Research Design

Research design is an overall plan for conducting a study, which provides procedures for collecting, analysing, interpreting, and reporting the findings of the research (Creswell & Plano Clark, 2007). Furthermore, the research questions will be addressed within the research design (Grey, 2014). According to Robson (2002), based on the research purpose, there are three main types of research design: descriptive research, exploratory research, and less common explanatory research.

3.3.1 Explanatory Research

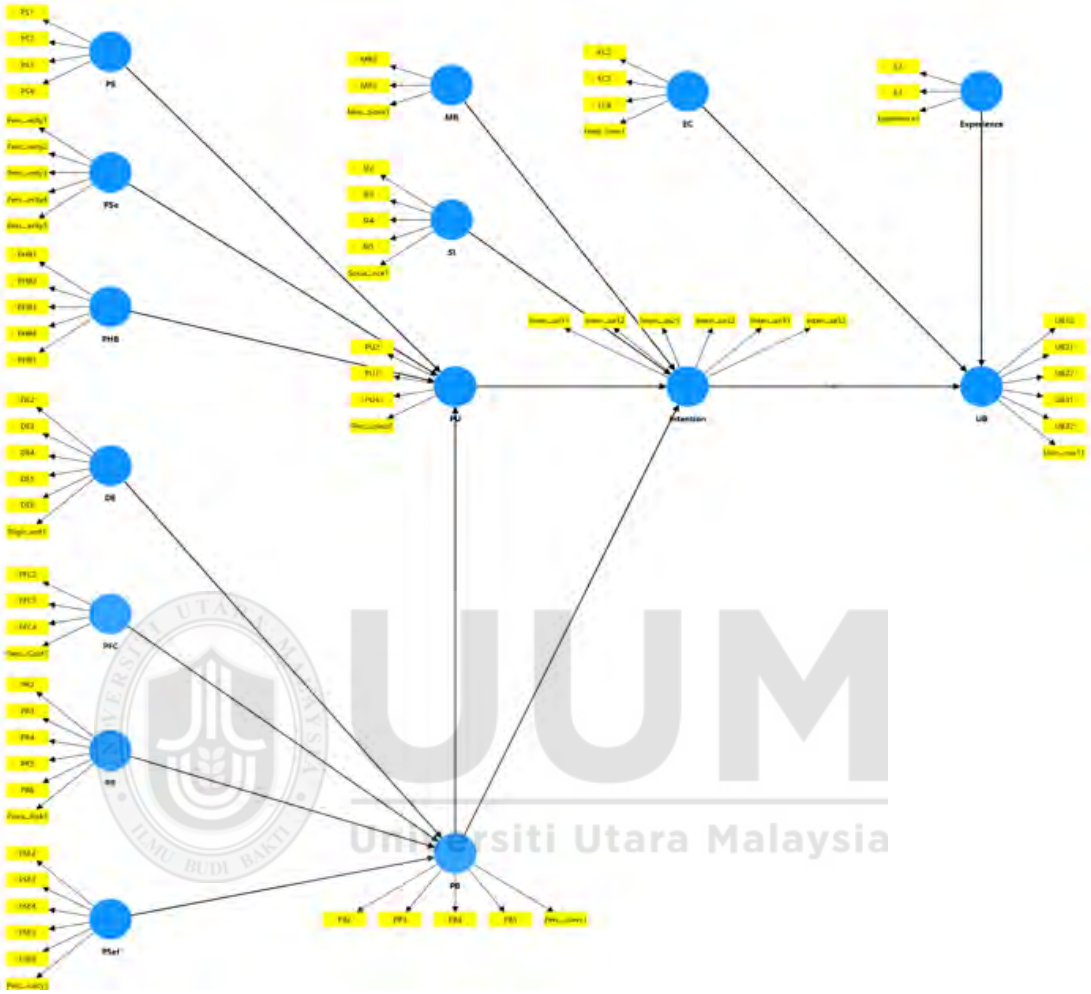
This study adopts an explanatory research design, aiming to explore the driving mechanism behind the use of new retail technology by different generations in China and the causal structure underpinning it. Unlike descriptive research, which mainly addresses what happened (What), explanatory research focuses on why and how it happened (Why & How), emphasising the causal pathways and theoretical verification between variables (Grey, 2014; Blumberg et al., 2005). Therefore, based on well-established theories such as the UTAUT unified theory, the health belief model (HBM), and the theory of resistance to technology (TORAOA), this study constructs

a path model that influences consumers' perceived usefulness, perceived resistance, intention to utilise, and actual behaviour, systematically explaining how health, financial, social, and technological factors impact the adoption of new retail technology.

This study adopts a positivist research philosophy (Positivism) and employs the deductive reasoning approach. In other words, hypotheses are initially proposed based on theories and then tested through the collection of quantitative data. Data was gathered using structured questionnaires that covered various new retail technology scenarios, such as self-service checkout, instant retail, and e-commerce assistants. Structural equation modelling (SEM) was utilised for path analysis and causal testing. Participants included China's Generation Y (born 1981-1996) and the Baby Boomer generation (born 1946-1964), with the aim of comparing the similarities and differences in their psychological mechanisms and behavioural patterns when using digital retail technology. The goal was to explore how technology adaptation and cultural differences across generations influence consumer behaviour.

The data collection employed a cross-sectional design, meaning the sample data was gathered at a single time point, using a self-administered questionnaire. This approach offers advantages such as manageable costs, simplicity of operation, and extensive sample coverage, which can effectively enhance the representativeness and analyzability of the data. Concurrently, expert review and pre-testing were conducted during the initial stage of questionnaire development to ensure it was linguistically clear, culturally adaptable, and measurement consistent across both elderly and young groups. The use of quantitative research not only aids in identifying significant relationships between variables but also uncovers key driving factors through model

fitting and effect analysis, thereby providing a scientific basis for the technical design and user segmentation of new retail.



3.4 Sampling Design

In the research field, the population refers to the total group of individuals with characteristics relevant to the research goal when people aim to achieve a specific research objective (Sekaran & Bougie, 2016). According to Banerjee and Chaudhury (2010), a statistical population not only consists of people but also includes additional information that needs investigation. Therefore, in descriptive research, the study population is defined by various characteristics the researcher wants to examine, such as geographic location, age, sex, occupation, religion, ethnicity, or other relevant

factors (Banerjee et al., 2007). A sample is a subset of the entire population as defined. The observed or examined sample is selected from the study population to represent the study. For this research, the concepts of population and sample align with the work by Banerjee and Chaudhury (2010), where the population includes the elderly population and Generation Y in Shanghai, and the sample is a subset of individuals chosen from this population.

3.4.1 Target Place

According to Savills Research (2019), Shanghai ranks as the leading retail city among twenty cities in China, including Beijing, Shenzhen, Chengdu, Hangzhou, Guangzhou, Chongqing, Wuhan, Nanjing, Tianjin, and others. In 2020, retail sales of consumer goods in Shanghai reached 1.59 trillion yuan, reflecting a 0.5% increase from 2019 (Xinhuanet). Additionally, numerous new retail stores have been opened in Shanghai, such as Alibaba's Fresh Hema supermarket, Starbucks Reserve Roastery, MAC Experience Centre, Dr Ci: Labo Spa, Luckin Coffee, and others. Consequently, this research was conducted in Shanghai City.

3.4.2 Population

Survey research sampling strategies aim to gather a sufficient sample to represent the study population (Ponto, 2015). The targeted respondent population for this study is people who stayed in Shanghai city. Respondents will be randomly selected from consumers of different age groups. The population of Shanghai is approximately 21,020,000 people. Only Gen Y and baby boomers meet the research requirements. In China, population ageing is an increasingly serious issue. According to data from Statista (2023), the proportion of people aged 65 and above is gradually increasing and

is expected to surpass the population of children aged 0-14 (Figure 3.1). This shows that the elderly population is growing rapidly, while the proportion of the younger population is relatively declining. In this regard, this study aims to examine the technological challenges faced by the elderly, particularly in the post-pandemic period, where the extent of their declining abilities has not yet been identified.

This study focuses on Generation Y (1981 to 1996), the first group of digital natives. During their development, Generation Y experienced ongoing technological shifts—from dial-up Internet access and feature phones to smart mobile devices—forming a highly consistent digital cognitive framework and operational experience (Tapscott, 2009). This generation exhibits a high level of familiarity, tolerance, and willingness to adopt new retail technologies (such as self-service checkouts, instant delivery, AR shopping guides, and social e-commerce). They can be regarded as lead users in the digital society. They serve not only as the core users (user core) of retail enterprises but also as creators (designer core) of retail design and as digital translators (guides) for family technology.

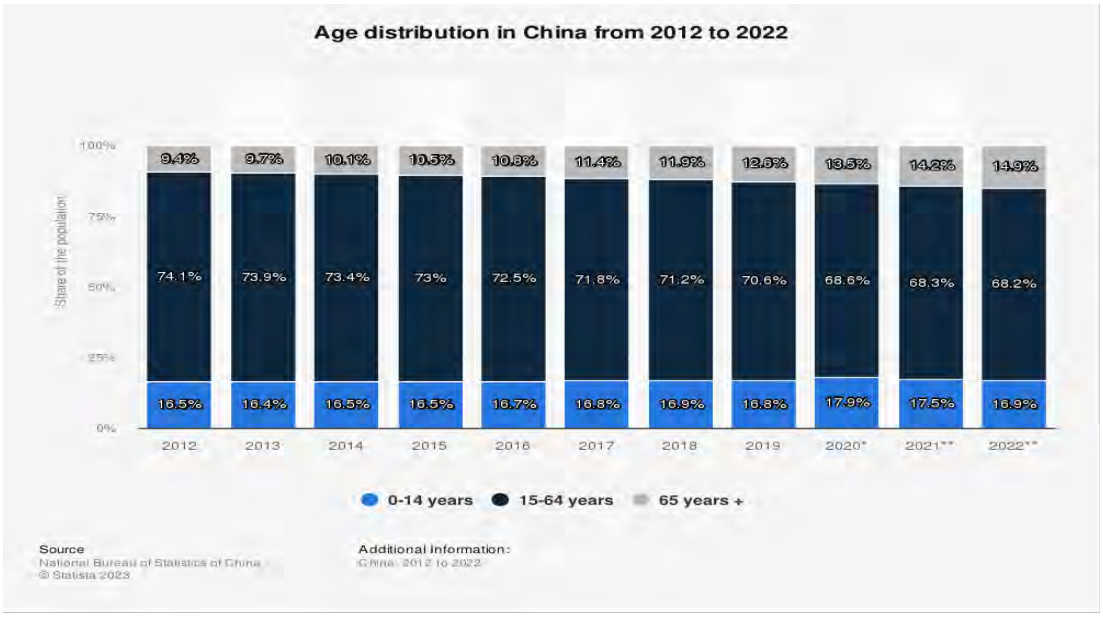


Figure 3.1 Age Distribution in China by Statista (2023)

3.4.3 Sampling Size

As Sekaran (2003) stated, sampling techniques involve selecting the appropriate number of samples to complete the experimental process and draw conclusions. Sampling offers a convenient method for researchers to obtain data results through collecting and analysing less data (Saunders et al., 2009). As Ponto (2015) explained, sampling is the process of using representative individuals to reflect the entire population. Therefore, the focus shifts to determining the number of representative individuals needed. Malhotra (2005) argues that determining the sample size is not arbitrary and should be based on tools or best practices derived from previous research.

Based on Krejcie and Morgan's table (Krejcie & Morgan, 1970), a sample size of 384 is sufficient for a population of approximately 21,000,000 to achieve results at a 99% confidence level with a 5% error margin. Table 3.1 displays the Krejcie and Morgan table and the corresponding sample size. According to Kim (2021), a larger sample size is advantageous for attaining data saturation. As described in a study, the discrepancy between the sample and the population diminishes as the sample size increases (Creswell, 2005). To minimise research error and reduce the impact of unique samples, the study selected 400 respondents (200 Baby Boomers (1944-1964) and 200 Gen Y (1981-1996)).

The widely used scale for determining sample size is based on the seminal work of Krejcie and Morgan (1970). This study respects the majority's choice, although it is worth noting that other sample size calculations produce similar results.

N	S	N	S	N	S
10	10	220	140	1200	291
15	14	230	144	1300	297
20	19	240	148	1400	302
25	24	250	152	1500	306
30	28	260	155	1600	310
35	32	270	159	1700	313
40	36	280	162	1800	317
45	40	290	165	1900	320
50	44	300	169	2000	322
55	48	320	175	2200	327
60	52	340	181	2400	331
65	56	360	186	2600	335
70	59	380	191	2800	338
75	63	400	196	3000	341
80	66	420	201	3500	346
85	70	440	205	4000	351
90	73	460	210	4500	354
95	76	480	214	5000	357
100	80	500	217	6000	361
110	86	550	226	7000	364
120	92	600	234	8000	367
130	97	650	242	9000	368
140	103	700	248	10000	370
150	108	750	254	15000	375
160	113	800	260	20000	377
170	118	850	265	30000	379
180	123	900	269	40000	380
190	127	950	274	50000	381
200	132	1000	278	75000	382
210	136	1100	285	1000000	384

Note: N is population size; S is sample size (Source: Krejcie & Morgan, 1970)

Figure 3.2 Determining Sample from A Population

3.4.4 Sampling Technique

3.4.4.1 Non-Probability Sampling

The study employed non-probability sampling. Among the limitations of both non-probability and probability sampling, probability sampling targets a limited number of groups and all identifiable individuals (Vehovar et al., 2016). Probabilistic sampling guarantees that everyone has an equal chance of being selected, which reduces the influence of chance on research outcomes (Acharya et al., 2013). However, achieving probability sampling can be challenging for populations within a province or city (Acharya et al., 2013). Non-probability sampling involves selecting a number of groups from the total population that meet the research criteria, without requiring each sample to have an equal probability of selection (Ayhan, 2011).

3.4.4.2 Convenience Sampling

This study employs convenience sampling, which is a non-probability sampling method. It is a practical approach for quickly acquiring samples from easily accessible and readily available sources of participants (Curtis, 2011). Compared to probability sampling, convenience sampling offers advantages of saving time and costs and enhancing research efficiency without compromising the effectiveness of preliminary exploratory research (Westfall, 2009). Since this study involves two specific generational groups (Generation Y and Baby Boomer), the researchers opted to distribute questionnaires in locations where the elderly are relatively concentrated or where young people frequently gather.

In the specific operation process, the researchers distributed questionnaires on-site at several elderly activity centres in Shanghai to collect data from the Baby Boomer generation, while the samples of Generation Y came from shopping mall rest areas, parks, cafes, and other places where young people gather. The common characteristics of the above-mentioned locations are convenient interview opportunities, high personnel mobility, and easy access to samples, which conform to the basic principles of convenience sampling.

To ensure that the research participants meet the basic age requirements, the researchers will first use brief questions to preliminarily determine the respondents' generational affiliation before distributing the questionnaires, such as confirming their age group prior to proceeding. Throughout the entire distribution process, the researchers explained the purpose of the study and how to fill in the questionnaire to the respondents, emphasising the importance of providing accurate information. During the filling process, the researchers remained on site, supplied basic tools (such

as pens and paper questionnaires), and provided brief explanations when respondents asked questions, attempting to avoid guiding language to maintain the objectivity of the data.

It should be emphasised that this study did not intentionally screen individuals who had used new retail technologies during the sample recruitment process. The aim was to gather authentic perceptions and usage intentions from both users and non-users simultaneously, thereby enriching the explanatory power between perceived barriers and usage behaviour in the model. This approach helps to capture a more comprehensive technology adoption pathway and provides more valuable empirical evidence for the suitability of new retail for the elderly user group.

3.5 Research Instruments and Measurements

Survey questionnaires were used as the research instrument in this study to collect data. A survey questionnaire can accommodate many respondents and provide ample data for the researcher (Kim, 2013).

3.5.1 Self-Administered Questionnaire (SAQ)

A self-administered questionnaire will be designed and distributed to the relevant respondents once the supervisor approves. The self-administered questionnaire can be completed independently by respondents, reducing the researchers' interference and enhancing respondents' ability to complete it (Lavrakas, 2011). In this study, the electronic format of the questionnaire limited direct intervention or assistance from the researchers.

As a result, respondents were required to complete the questionnaire independently. To ensure its effectiveness, the questionnaire must possess certain characteristics. It should be easy to understand, free from ambiguity, and aligned with normal human cognition. According to Jenkins and Dillman (1995), an SAQ is a simple questionnaire that can be completed independently without assistance. It is crucial to avoid situations where the questionnaire issuer or researchers influence respondents' answers or lead them to deviate from their true thoughts. Such interference may introduce biases and undermine the validity of the research. The questions included in the questionnaire directly affect respondents' answers and can significantly impact the research outcomes (Kim, 2017).

Self-administered questionnaires are regarded as an efficient and cost-effective method for collecting information compared to other approaches (Jenkins & Dillman, 1995). Moreover, fixed-alternative response format questions are designed to enhance the reliability of respondents' answers. This format also facilitates easier analysis of the collected data for researchers.

3.5.2 Electronic and Paper Questionnaires

This study chose to use both an electronic questionnaire and a traditional paper questionnaire. An electronic questionnaire involves distributing and collecting responses via social media platforms or other information communication technologies (Kiesler & Sproull, 1986). Compared to traditional paper questionnaires, electronic ones provide several benefits. A main advantage is that they utilise the internet's information dissemination capabilities, removing the restriction of geographical location. Respondents and researchers can distribute, complete, and gather questionnaires regardless of their physical distance.

This approach notably decreases data collection time, labour, and financial costs (Trujillo, 2009). However, electronic questionnaires also have certain disadvantages. One significant limitation is their rigidity. Researchers cannot gauge respondents' mental state, emotions, or whether they are in a leisure period when completing the questionnaire. Respondents might complete the questionnaire with low motivation, which could affect the quality of their responses. Furthermore, researchers cannot determine if respondents experienced dyslexia or had difficulty understanding particular questions, leading to interpretative errors. Therefore, in the case of older adults, this study primarily uses paper-based questionnaires.

Content assessment is the initial step in designing a survey questionnaire. This process verifies the relevance and suitability of the items included. The questionnaire items incorporate various sets from related previous studies. Furthermore, advancements in internet technology have transformed the way researchers gather information and have streamlined the research process.

The online survey application enables a standardised format for presenting respondents' questions and responses (Crawford et al., 2005). Subsequently, a web-based survey will be chosen to administer the questionnaire. The web-based survey is transparent to respondents, and this new data collection method involves internet assessment. Forms are used to present the questionnaire, which will be distributed via e-mail or website. There are several advantages to using a web-based survey for research, including eliminating the need for an interviewer, reducing interviewer bias, lowering survey costs, and increasing survey efficiency by speeding up respondents' replies (Tina et al., 2000). Additionally, an offline survey form was also utilised for

the research. Therefore, this study employed two different data collection methods: online and offline.

The online survey utilised the Form platform to distribute questionnaires to respondents via WeChat. Respondents completed and returned the questionnaires using the same platform. In contrast, the offline survey involved printing the questionnaires and distributing them to targeted respondents. After completion, the physical questionnaires were returned to the researcher. A total of 150 electronic questionnaires were collected, while the remaining 250 were paper questionnaires, as many elderly people in China generally lack mobile devices. An excessive number of electronic questionnaires could introduce biases in PB.

3.5.3 Five-Point Likert Scale

Rensis Likert created a psychological scale in 1932 that allows respondents to express their attitudes based on their level of agreement or disagreement. This scale has been widely utilised in psychological research to assess individuals' opinions or attitudes (Likert, 1932).

Subsequently, the Five-Point Likert Scale is used to measure all the questions. The rating scale with 1 means strongly disagree, 2 means disagree, 3 means slightly agree, 4 means agree and 5 means strongly agree.

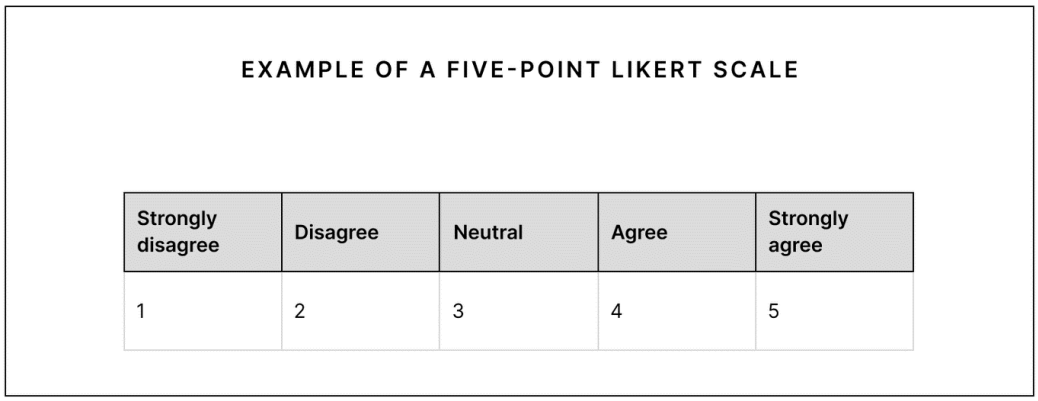


Figure 3.3 Five-Point Likert Scale by Culture Amp (2023)

3.5.4 Questionnaire Design

Questionnaire design is crucial because it influences the reliability, effectiveness, and alignment with the research objectives of the study outcomes. In this context, this study carefully selected the research questionnaire to minimise biases. Additionally, it conserves time and financial resources, as there is no need for pre-tests and pilot tests to verify the suitability of unproven scales for the research aims. Such testing generally involves confirming clarity of expression, addressing collinearity issues, assessing reliability, establishing construct validity, and considering ethical aspects. When using established scales, researchers can benefit from the extensive testing and validation these scales have already undergone.

The questionnaire content is adapted from relevant literature related to this study's variables. The questionnaire consists of two sections: Section A and Section B. Section A gathers biographical information about respondents, such as age, gender, ethnicity, and educational level. This section helps researchers better understand the

demographic characteristics of the respondents. Section B asks questions regarding the variables of this research.

The variables include PSU, PSE, PHB, PB, PU, SI, DE, PFC, PR, SR, ITU, MR, FC, UB, and PS. The questionnaire consists of 59 questions related to these variables in the research topic. All questions are formulated positively.

Table 3.1
Questionnaire Source

No.	Variable	N	Sources
1.	PSU	3	Daragmeh and Zéman (2021).
2.	PSE	3	Daragmeh and Zéman (2021).
3.	PHB	8	Gumasing et al. (2022).
4.	DE	3	Researcher setting
5.	PFC	4	Tan et al. (2010).
6.	PR	4	Tan et al. (2010).
7.	PS	3	Daragmeh and Zéman (2021).
8.	PB	5	Gumasing et al. (2022).
9.	PU	3	Daragmeh and Zéman (2021).
10.	SI	5	Gumasing et al. (2022).
11	MR	3	Gray-Miceli (2017).
12.	FC	4	Gumasing et al. (2022).
13.	ITU	2	Gumasing et al. (2022).
14.	Experience	3	Venkatesh and Davis (2000).
15.	UB	2	Gumasing et al. (2022).

3.6 Pilot Test and Pre-Test Data Collection Procedures

Before conducting a survey in research, a pilot test serves as a small-scale preliminary study undertaken to assess the proposed research. The pilot test follows the same process and procedures as the actual survey to examine the feasibility of the research. Some prior literature (Magnusson & Marecek, 2015) explains that researchers gather helpful feedback from pilot test participants to improve the questions, making them more transparent and precise. Therefore, the pilot test is essential for evaluating the questionnaire before distribution to respondents for data collection. It ensures that the questions are understandable and relevant to the research objectives. Additionally, the pilot test helps the researcher identify errors in the questions that might lead respondents to biased answers. Similarly, Sekaran (2003) describes a pilot test as a procedure to ensure that respondents' words, phrases, and the sequence of questions are comprehensible. Consequently, the pilot test is vital for preventing misinterpretation of questions and misconceptions about the study's purpose. Furthermore, some studies suggest that researchers often need to conduct a pilot test to identify potential obstacles during the operational process, which could lead to research failure or costs not aligning with expectations (Moore et al., 2011).

The questionnaire reviewed by the researcher's supervisor was used for a pilot test. A pilot test is a trial run of the questionnaire with a small sample of targeted respondents. All comments and feedback from pilot test participants will be collected and analysed. According to Hill and Williams (2012), an ideal sample size for a pilot test includes 10 to 15 participants, while Hertzog (2008) and Connelly (2008) suggested that 10% of the total sample size of a full-scale study would be sufficient to run a pilot test.

A sample of 40 individuals was selected from the targeted population for the pilot test to assess whether the respondents understood the questionnaire and met the research objectives. An offline survey form and an online survey were used for the pilot test. For the offline survey method, the questionnaire was printed and distributed to pilot test participants. In contrast, for the online survey, the questionnaire was distributed through a website or email.

The data from the returned questionnaire will be transferred and analysed using the Statistical Package for Social Sciences (SPSS). Data errors such as outliers and missing values should be assessed through data screening. Additionally, the participants of the pilot test were not included in the main survey of the research. The pilot test was conducted over two weeks to gather all feedback. Questions were adjusted based on the results obtained from the pilot test. Following peer review and evaluation of the respondents' questionnaire feedback, the updated questionnaire is as follows:

Drafting the Initial Questionnaire: Based on the theoretical model and research variables, along with the literature review and research objectives, the researchers designed the first version of the questionnaire, including the content of the items, the form of the scale, and the language style.

Expert Review Pre-Test: The initial draft questionnaire was submitted to the instructor and three specialists in digital technology and elderly research for evaluation. The experts concentrated on the following aspects:

- Whether it meets the measurement purpose
- Whether the language and cultural expression are appropriate

- Whether the order of questions is smooth and whether there is a sense of jump
- Whether the terminology is too professional or causes misunderstanding

Small-Scale Field Pre-Test: Ten target groups, each consisting of five baby boomers and five Gen Y participants, were selected to complete the questionnaire face-to-face. Their response times, comprehension difficulties, and psychological reactions were observed, and feedback and suggestions were gathered through interviews. This stage aims to identify:

- Which items are difficult to understand
- Which expressions are too complex or indirect
- Which questions cause emotional or logical barriers

Questionnaire Revision and Optimisation: Based on expert opinions and actual test feedback, the questionnaire is semantically modified, the order is adjusted, and the items are deleted or reconstructed to ensure that it has:

- The language is easy to understand
- The logical structure is reasonable
- The content meets the measurement objectives
- It is highly consistent with the cultural context

Finalisation and Validation: Review the revision results with experts and obtain their approval, and finally form a formal version of the questionnaire.

Additional description of the number of questionnaires: Hair et al. (2010) stated that the more items each variable has, the more conducive it is to express the concept of the item and its identifiability clearly. The number of items in the original questionnaire is empirical, and appropriately expanding the number of items can enhance content validity and conceptual coverage (DeVellis, 2016). Therefore, this study refined the number of measurement items for the variables appropriately and provided a basis for further refinement.

The expert group's feedback on the original questionnaire: The original questions focused on the specific case of SARS-CoV-2, which does not reflect the characteristics of many other common infectious diseases after the pandemic. The use of cash and physical contact is not specific or clear, and elderly respondents may not understand these terms well. The original instrument emphasises the patient's fear emotion, which is too subjective. The risks and hazards posed by the disease should comprise both objective and subjective elements, with clear characteristics, particularly for the elderly. In PSU, PSE, and PHB, many items are merely synonyms and do not measure perceptions at different levels. The original questionnaire concentrated more on cash and supermarkets and did not adequately reflect the key technologies in the new retail scenario. The emotional expressions in the original questions are not conducive to behaviour prediction or quantitative modelling. Some variables are assessed with only 2-3 items, which is insufficient to capture the dimensions of the latent variable fully.

Table 3.2
Self-Administered Questionnaire (SAQ) Revision (PSU)

Before revision	After revision
There is a possibility of getting infected by SARS-CoV-2 due to using cash or physical contact buying behaviour (Daragmeh et al., 2021).	Using cash payments may increase the risk of contracting infectious diseases.
My chances of being infected by SARS-CoV-2 if I use cash or physical contact buying behaviour are high (Daragmeh et al., 2021).	Meeting cashiers may pose a risk of infectious diseases.
I feel that SARS-CoV-2 will develop health problems for me in the future (Daragmeh et al., 2021).	I feel that other shoppers in the supermarket may cause me to contract infectious diseases.
	Protective measures may not prevent the attack of some infectious diseases.

Table 3.3
Self-Administered Questionnaire (SAQ) Revision (PSE)

Before revision	After revision
Thinking about getting infected by SARS-CoV-2 due to using cash or physical contact buying behaviour makes me nervous (Daragmeh et al., 2021).	Infectious diseases, such as influenza A, influenza B, and pandemics, are difficult to cure completely.
I am afraid to think about the health problems of getting infected by SARS-CoV-2 if I use cash or physical contact buying behaviour (Daragmeh et al., 2021).	Infectious diseases, such as influenza A, influenza B, and pandemics, may cause some lifelong diseases.
If I get infected by SARS-CoV-2 due to using cash or physical contact buying behaviour, my whole life will change (Daragmeh et al., 2021).	Infectious diseases like influenza A, influenza B, and the pandemic may affect my health.
	I feel that c will worsen my other illnesses, such as Influenza A, Influenza B, and Pandemic.

	Infectious diseases such as influenza A, influenza B, and the pandemic have a fatality rate.

Table 3.4
Self-Administered Questionnaire (SAQ) Revision (PHB)

Before revision	**After revision**
Using online grocery apps reduces my chance of infection	Online supermarkets reduce my contact with cashiers and other supermarket staff, reducing the risk of infectious diseases.
Using online grocery apps decreases the severity and the chance of complications if I get infected with COVID-19.	Self-checkout systems reduce my contact with cashiers, reducing the risk of infectious diseases.
Using online grocery apps helps me to avoid contact with other people and crowded places.	When I have infectious diseases, online supermarkets and self-checkout systems reduce the harm I pose to society.
I want to adhere to the principles of prevention and government restrictions.	Online supermarkets and self-checkout systems reduce the waiting time in supermarket checkout queues and the crowd density in enclosed spaces, reducing the risk of infectious diseases.
Using the self-checkout service reduces my chance of infection	Online supermarkets and self-checkout systems comply with national and local government management policies.
Using self-checkout service decreases the severity and the chance of complications if I get infected with COVID-19.	
Using self-checkout service helps me to avoid contact with other people and crowded places.	
I want to adhere to the principles of prevention and government restrictions.	

Table 3.5
Self-Administered Questionnaire (SAQ) Revision (DE)

Before revision	**After revision**

I own a new retail-enabled device.	I have at least one smartphone, tablet, or computer.
I can use my device and make purchases anytime and anywhere if Internet-enabled.	I can access new retail platforms with an internet connection if I need to.
My device has an acceptable level of lag when using e-retail services	My devices have an acceptable level of latency when using electronic retail services.

Table 3.6
Self-Administered Questionnaire (SAQ) Revision (PFC)

Before revision	**After revision**
New retail makes me spend more on equipment.	Compared to traditional in-person shopping, new retail requires me to spend more money on devices.
New retail makes me spend more on merchandise ordering services	Compared to traditional in-person shopping, new retail requires me to spend more money on product purchase services.
New retail makes me spend more on internet connectivity	Compared to traditional in-person shopping, new retail requires me to spend more on internet connectivity.
New retail makes me spend more on product shipping	Compared to traditional in-person shopping, new retail requires me to spend more on product delivery.

Table 3.7
Self-Administered Questionnaire (SAQ) Revision (PR)

Before revision	**After revision**
I am concerned about the theft of payment-related information	After downloading the retail service app, I suspect that my payment-related information has been (or will) stolen.
I suspect about the theft of search-related information	After downloading the retail service app, I suspect that my search-related information has been (or will) stolen.
I suspect the theft of voice chat-related information	After downloading the retail service app, I suspect that my voice chat-related information has been (or will) stolen.

I suspect about the theft of information related to browsing history	After downloading the retail service app, I suspect that my browsing history-related information has been (or will) stolen.
	After downloading the retail service app, I suspect my personal information was stolen.
	After downloading the retail service app, I suspect my actions are(or will) being monitored.

Table 3.8
Self-Administered Questionnaire (SAQ) Revision (PS)

Before revision	**After revision**
It would be easy for me to learn how to use new retail systems.	For me, it is easy to learn how to use the new retail system.
I could use an e-wallet if someone showed me how to do it.	I can understand the key components and settings of the new retail system.
I can use an e-wallet if no one is around to tell me what to do.	I won't make too many operational mistakes.
	I can use the self-checkout function independently.
	I can shop independently using the online supermarket function.
	I can communicate independently with the e-commerce intelligent assistant.

Table 3.9
Self-Administered Questionnaire (SAQ) Revision (PB)

Before revision	**After revision**
I do not have the patience to follow COVID-19 precautionary measures	I am concerned about the cost of using the new retail system.
It isn't easy to follow the COVID-19 prevention recommendations	I am concerned about the privacy risks of the new retail system.
I find it challenging to wash my hands with soap and water repeatedly	I am concerned about the difficulties of using the new retail system.

It is tough to avoid touching your hands, lips, nose, or eyes	I am concerned about the reliance of the new retail system on electronic devices.
A face shield is inconvenient to use and uncomfortable	I cannot use the new retail system well.

Table 3.10
Self-Administered Questionnaire (SAQ) Revision (PU)

Before revision	**After revision**
Using the new retail system improves my performance in managing personal payments.	The new retail system improves the efficiency of purchasing.
the new retail system saves time in making payments	The new retail system improves the quality of services.
overall, the new retail system helps manage payments	The new retail system reduces the risk of the pandemic.
	The new retail system is effective in meeting demands.

Table 3.11
Self-Administered Questionnaire (SAQ) Revision (SI)

Before revision	**After revision**
My family members believe that ordering groceries online is a great idea.	My family recommended the new retail system, such as e-commerce assistants, just-in-time retail or self-checkout technology.
Most acquaintances and friends think buying groceries online is an excellent idea.	My friends recommended the new retail system, e-commerce assistants, just-in-time retail or self-checkout technology.
In my community, shopping for groceries online is a status symbol.	Using the new retail system is an essential skill in my community.
People who sway my decisions believe that I should shop for groceries online.	People who influenced my decision think I should use e-commerce assistants, just-in-time retail or self-checkout technology.
People around me think it is perfectly acceptable to shop for groceries online.	People around me believe that e-commerce assistants and just-in-time retail or self-checkout technology are entirely acceptable.

Table 3.12
Self-Administered Questionnaire (SAQ) Revision (MR)

Before revision	**After revision**
Going to stores is not easy for me.	It's not easy to go to a store and go through the shopping process.
I cannot easily access transportation.	I cannot easily access transportation.
Going to the store and returning with items requires time and effort.	Going to the store and returning with items requires much time and effort for me.

Table 3.13
Self-Administered Questionnaire (SAQ) Revision (FC)

Before revision	**After revision**
I have the necessary resources to shop in an online grocery store.	I can search for 4G (5G) networks at my location and local stores, and there are usually no power outages.
I have the essential skills to shop for groceries online.	I have online banking services that support the new retail system.
When I have problems using an online grocery app, a specialised person (or group) can help me.	The other technologies I use are compatible with online grocery shopping.
Other technologies I use are compatible with online grocery shopping.	The supermarket provides self-checkout machines.
	There is an ample supply of self-checkout machines in the supermarket.
	Online supermarkets are equipped with e-commerce intelligent assistants.

Table 3.14
Self-Administered Questionnaire (SAQ) Revision (ITU A)

Before revision	**After revision**
I am willing to use online supermarkets as an alternative to in-person shopping.	I am willing to use online supermarkets as an alternative to in-person shopping.
Compared to traditional in-person shopping, I prefer online supermarkets.	Compared to traditional in-person shopping, I prefer online supermarkets.

Table 3.15
Self-Administered Questionnaire (SAQ) Revision (ITU B)

Before revision	**After revision**
I am willing to use the e-commerce intelligent assistant to communicate and negotiate with stores.	I am willing to use the e-commerce intelligent assistant to communicate and negotiate with stores.
Compared to face-to-face communication, I prefer communicating and negotiating with the e-commerce intelligent assistant.	Compared to face-to-face communication, I prefer communicating and negotiating with the e-commerce intelligent assistant.

Table 3.16
Self-Administered Questionnaire (SAQ) Revision (ITU C)

Before revision	**After revision**
I am willing to use self-checkout systems.	I am willing to use self-checkout systems.
Compared to traditional waiting in line for a cashier, I prefer self-checkout systems.	Compared to traditional waiting in line for a cashier, I prefer self-checkout systems.

Table 3.17
Self-Administered Questionnaire (SAQ) Revision (Experience)

Before revision	**After revision**
I have experience using online supermarkets.	I have experience using online supermarkets, e-commerce intelligent assistants and self-checkout systems.
I have experience using e-commerce intelligent assistants.	I have tried these techniques before.
I have experience using self-checkout systems.	I will never forget how to use them.

Table 3.18
Self-Administered Questionnaire (SAQ) Revision (UB A)

Before revision	**After revision**
I frequently use online supermarkets.	I frequently use online supermarkets.

I will continue to use online supermarkets.	I will continue to use online supermarkets.

Table 3.19
Self-Administered Questionnaire (SAQ) Revision (UB B)

Before revision	**After revision**
I frequently use e-commerce intelligent assistants.	I frequently use e-commerce intelligent assistants.
I will continue to use e-commerce intelligent assistants.	I will continue to use e-commerce intelligent assistants.

Table 3.20
Self-Administered Questionnaire (SAQ) Revision (UB C)

Before revision	**After revision**
I frequently use self-checkout systems.	I frequently use self-checkout systems.
I will continue to use self-checkout systems.	I will continue to use self-checkout systems.

Minor modifications were made to ensure that the scales used in this study are appropriate for the Chinese context. China, a high-context country according to Hofstede's cultural dimensions, is known for its relatively reserved communication style (Men & Tsai, 2012). These modifications were based on the results of direct and telephone interviews conducted with classmates and the interviewee group.

3.7 Unit of Analysis

According to Cavana et al. (2001), the unit of analysis is the extent of data collected in the next stage of data analysis. In this study, the unit of analysis is the Gen Y and baby boomers living in Shanghai, China. This means the unit of analysis is a consumer.

The study examines the influence of independent variables such as PSU, PSE, PHB, PB, PU, social influence, digital equipment, perceived financial cost, privacy risk, intention to use, facilitating conditions, and perceived self-efficacy on the adoption of new retail.

3.8 Validity and Reliability

Validity is the best available approximation to the truth of a given inference, proposition or conclusion (Chruch et al., 2007). The validity test aims to assess the suitability of the questionnaire survey content and determine whether the questions align with the research objectives outlined in this study. Therefore, validity is also regarded as a measure of measurement precision, indicating the extent to which the research accurately evaluates the concept the researcher intends to investigate (Sireci & Faulkner-Bond, 2014; Pilot & Hungler, 1999).

According to Creswell & Creswell (2018), there are two methods to assess validity: construct validity and content validity. Content validity is evaluated subjectively at one's discretion. Then, content validity is carried out during the pilot test through the revision process, analysing and collecting feedback from selected respondents to determine whether the questions match the correct variable of interest (Hair et al., 2010; Anderson, 2009). Furthermore, the literature was also used to examine whether the questionnaire content best represents each variable (Sireci & Faulkner-Bond, 2014).

An evaluation of the consistency between various variable measurements is known as reliability (Hair et al., 2010). Therefore, the reliability test assesses the level of random errors affecting the values (Sekaran & Bougie, 2016). Cronbach (2004) suggested that

Cronbach’s coefficient alpha explains the reliability of measurements in empirical research. Consequently, Cronbach’s alpha was used to examine the reliability of each variable in this study. The values of Cronbach’s coefficient alpha range from 0 to 1. A higher Cronbach’s alpha indicates greater reliability of the constructed questions. An acceptable alpha value for reliability is at least 0.7. If the coefficient alpha is lower than 0.7, the questionnaire items should be discarded. Additionally, this study employed KMO and Bartlett's Test for validity analysis. The results from the initial sample of 40 are as follows:

Table 3.21
Validity and Reliability Tests

Variable	N	Cronbach's Alpha	KMO	Sig.
Perceived Susceptibility	4	.862	.766	.000
PSE	5	.737	.723	.000
PHB	5	.768	.699	.000
Digital Equipment	3	.814	.787	.000
Perceived Financial Cost	4	.858	.798	.000
Privacy Risk	6	.794	.824	.000
Perceived self-efficacy	6	.764	.843	.000
PB	5	.828	.748	.000
PU	4	.877	.923	.000
Social Influence	5	.834	.945	.000
Movement restrictions	3	.888	.826	.000
Facilitating conditions	6	.859	.937	.000
Intention to use a	2	.911	.889	.000
Intention to use b	2	.823	.811	.000

Intention to use c	2	.845	.822	.000
Experience	3	.815	.877	.000
Using behaviour a	2	.713	.818	.000
Using behaviour b	2	.825	.822	.000
Using behaviour c	2	.800	.811	.000

3.9 Ethics Review

The research strictly adheres to Chinese law and UUM ethical review requirements. Before distributing the questionnaire, the supervisor must approve the SAQ. All respondents completed the questionnaire voluntarily and were not coerced in any way. Respondents were informed about the content and purpose of the study prior to filling out the questionnaire.

Detailed description: This study adhered to ethical standards for data collection, including guidelines from ethics committees and standard ethical codes in China. The following aspects were addressed: (1) Dissemination of Questionnaire. The study provided essential information about the researchers, including contact details (WeChat, QQ), the researchers' surnames, the organisation's name, the educational institution's name, the research purpose, and the general content of the questionnaire. (2) Voluntary Participation. Questionnaires were collected only with the consent of the interviewees or interviewee groups. The researchers initiated the project after receiving positive feedback from the game company's product design and development department. Participation was voluntary, and respondents who declined to take part were not required to give reasons for their decision. (3) Freedom of Participation. Participants could choose not to complete the questionnaire at any point. After

completing it, they might also decide to have their personal information deleted. Participants did not need to justify their non-participation, and they were free from any fear of retaliation. This is not an exhaustive list. (4) Complete Questionnaires Without Bias. Data collectors could not influence participants' subjective thoughts in group or individual discussions.

The questionnaire was intended to be completed freely and without outside interference by the participants. The researcher did not provide any hints about the questions. (5) Anonymity. Because the questionnaire guaranteed anonymity, participants did not need to worry about their private information being accessed or viewed by unauthorised parties. Sensitive data, such as marital status, violence, pornography, moral principles, or psychiatric issues, were excluded from the survey. If participants wish to share their email, that is acceptable. (6) Reimbursement for participation. The study aimed to explore inexpensive ways to compensate participants. (7) Storage and confidentiality of data. The researchers were the only individuals with access to the data, which was securely stored on a USB flash drive. (8) After data analysis, all data was deleted and not used for any other purpose. By adhering to these ethical considerations, the study ensured participants' privacy, voluntary participation, and confidentiality, while maintaining transparency about the research process.

3.10 The Back Translation

To ensure the quality of the SAQ and minimise the difficulty of understanding caused by cultural and textual differences, the researchers utilised a bilingual questionnaire in both Chinese and English. In this regard, this study employs the back translation method to encode and translate the data. The back translation is an iterative comparison

process (PacMan100, 2018). The principle involves translating Chinese into English and then having another professional translate it back into Chinese. The consistency between the original Chinese content and the final Chinese content indicates the accuracy of the translation.

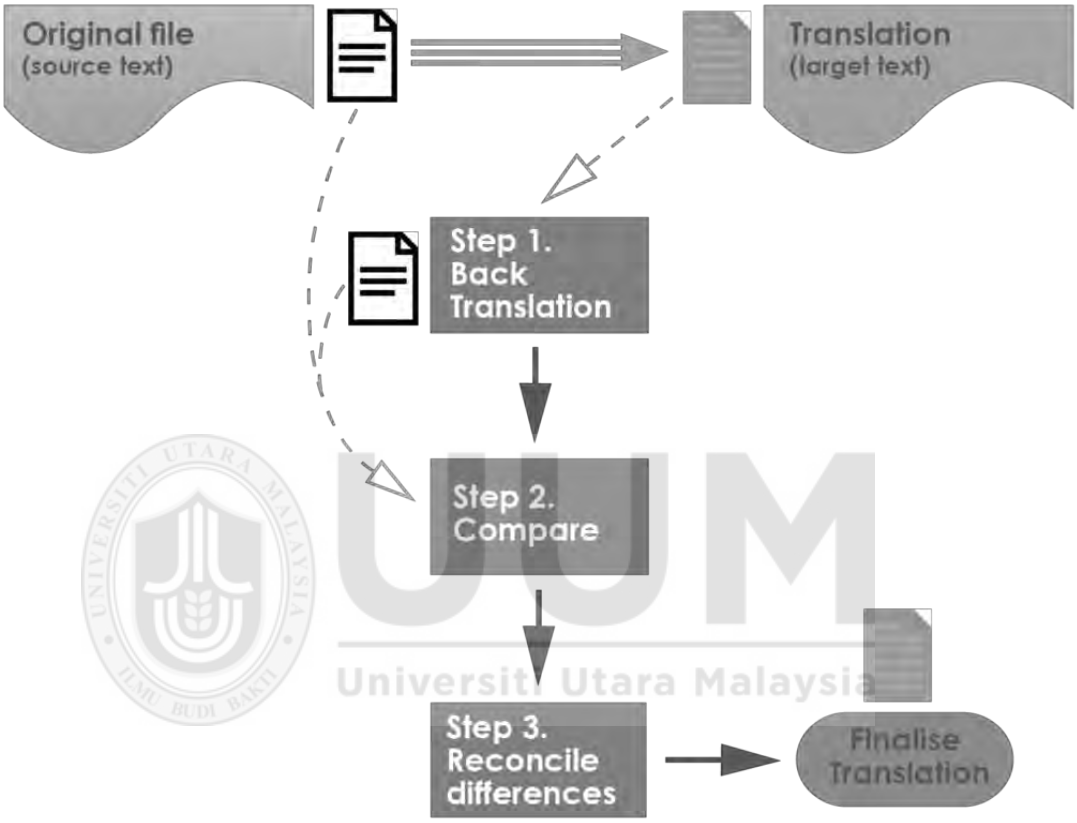


Figure 3.4 The Back Translation by https:andandwww.pactranz.comandback-translationand

Detailed description: English is not widely spoken or easily understood in China. According to data provided by China Highlights (2022), less than 1% of the total population in China can communicate in English without barriers. Therefore, an English questionnaire would not be suitable for the Chinese population. Instead, this study developed a Chinese questionnaire that aligns with the cultural characteristics of the target population. To ensure consistency between the Chinese and original English

questionnaires, reverse translation was used. Reverse translation has gained popularity due to its cost-effectiveness and relatively straightforward process. It involves two translators proficient in both Chinese and English languages.

Firstly, the first translator translates the English questionnaire into Chinese. Then, the second translator independently translates the Chinese questionnaire back into English. Finally, the researchers compare the original English questionnaire with the back-translated version to see if the meanings conveyed are consistent. The translation is considered valid and reliable if the questionnaire's content remains consistent. When conceptual differences arise in certain parts of the content, the two translators collaborate to revise and align the translations until consistency is achieved.

Table 3.22
Self-Administered Questionnaire (SAQ) Revision (PSU)

Before revision	After revision
I feel that using cash payments may lead to the risk of infectious diseases.	我觉得使用现金支付可能会有传染疾病的风险。
I feel that meeting cashiers may lead to the risk of infectious diseases.	我觉得接触收银员可能会有传染疾病的风险。
I feel that other shoppers in the supermarket may cause me to contract infectious diseases.	我觉得超市里的其他购物者可能会让我感染传染病。
I feel that protective measures may not be able to prevent the attack of some infectious diseases.	我觉得防护措施可能并不能阻止一些传染病的侵袭。

Table 3.23
Self-Administered Questionnaire (SAQ) Revision (PSE)

Before revision	After revision
Infectious diseases such as influenza A, influenza B, and a pandemic are challenging to cure completely.	我觉得传染病很难彻底治愈，比如甲型流感、乙型流感、流行病。

Infectious diseases may cause lifelong diseases, such as Influenza A, Influenza B, and Pandemic.	我觉得传染病可能会导致一些终生的疾病，比如甲型流感、乙型流感、大流行。
Infectious diseases such as Influenza A, Influenza B, and the Pandemic may affect my health.	我觉得传染病可能会影响我的健康，例如甲型流感、乙型流感、流行性感冒。
I feel that c will worsen my other illnesses, such as Influenza A, Influenza B, and Pandemic.	我觉得 c 会使我的其他疾病恶化，例如甲型流感、乙型流感、流行性感冒。
Infectious diseases such as influenza A, influenza B, and the pandemic have a fatality rate.	我觉得传染病是有致死率的，比如甲型流感、乙型流感、大流行。

Table 3.24
Self-Administered Questionnaire (SAQ) Revision (PHB)

Before revision	**After revision**
I feel that online supermarkets reduce my contact with cashiers and other supermarket staff, reducing the risk of infectious diseases.	我觉得网上超市减少了我与收银员和其他超市工作人员的接触，降低了感染疾病的风险。
I feel that self-checkout systems reduce my contact with cashiers, reducing the risk of infectious diseases.	我觉得自助结账系统减少了我与收银员的接触，降低了感染疾病的风险。
When I have infectious diseases, online supermarkets and self-checkout systems reduce the harm I pose to society.	我觉得当我患有传染病时，网上超市和自助结账系统减少了我对社会造成的危害。
Online supermarkets and self-checkout systems reduce the waiting time in supermarket checkout queues and the crowd density in enclosed spaces, reducing the risk of infectious diseases.	我觉得网上超市和自助结账系统减少了超市结账排队的等待时间和封闭空间的人群密度，降低了传染病的风险。
Online supermarkets and self-checkout systems comply with national and local government management policies.	我觉得网上超市和自助结账系统符合国家和地方政府的管理政策。

Table 3.25
Self-Administered Questionnaire (SAQ) Revision (Digital Equipment)

Before revision	**After revision**

I have at least one smartphone, tablet, or computer.	我至少有一部智能手机、平板电脑或电脑。
I can access new retail platforms with an internet connection if I need to.	如果需要，我可以在有互联网连接的情况下访问新零售平台。
My devices have an acceptable level of latency when using electronic retail services.	使用电子零售服务时，我的设备具有可接受的延迟水平。

Table 3.26
Self-Administered Questionnaire (SAQ) Revision (Perceived Financial Cost)

Before revision	**After revision**
Compared to traditional in-person shopping, new retail requires me to spend more money on devices.	与传统的面对面购物相比，我觉得新零售需要我在设备上花更多的钱。
Compared to traditional in-person shopping, new retail requires me to spend more money on product purchase services.	相比传统的亲自购物，我觉得新零售需要我花更多的钱在产品购买服务上。
Compared to traditional in-person shopping, new retail requires me to spend more on internet connectivity.	与传统的面对面购物相比，我觉得新零售需要我在网络连接上花费更多。
Compared to traditional in-person shopping, new retail requires me to spend more on product delivery.	与传统的面对面购物相比，我觉得新零售需要我在产品交付上花费更多。

Table 3.27
Self-Administered Questionnaire (SAQ) Revision (Privacy Risk)

Before revision	**After revision**
After downloading the retail service app, I suspect that my payment-related information has been (or will) stolen.	下载零售服务应用程序后，我怀疑我的支付相关信息已（或将）被盗。
After downloading the retail service app, I suspect that my search-related information has been (or will) stolen.	下载零售服务应用程序后，我怀疑我的搜索相关信息已（或将）被盗。
After downloading the retail service app, I suspect that my voice chat-related information has been (or will) stolen.	下载零售服务应用程序后，我怀疑我的语音聊天相关信息已（或将）被盗。

After downloading the retail service app, I suspect that my browsing history-related information has been (or will) stolen.	下载零售服务应用程序后，我怀疑我的浏览历史相关信息已（或将）被盗。
After downloading the retail service app, I suspect my personal information was stolen.	下载零售服务应用程序后，我怀疑我的个人信息被盗。
After downloading the retail service app, I suspect my actions are(or will) being monitored.	下载零售服务应用程序后，我怀疑我的行为正在（或将）受到监控。

Table 3.28
Self-Administered Questionnaire (SAQ) Revision (Perceived Self-Efficacy)

Before revision	**After revision**
For me, it is easy to learn how to use the new retail system.	对我来说，学习如何使用新零售系统很容易。
I can understand the key components and settings of the new retail system.	我能了解新零售系统的关键组成和设置。
I believe I won't make too many operational mistakes.	我相信我不会犯太多的操作错误。
I can use the self-checkout function independently.	我可以独立使用自助结账功能。
I can shop independently using the online supermarket function.	我可以使用网上超市功能独立购物。
I can communicate independently with the e-commerce intelligent assistant.	我可以独立与电商智能助手沟通。

Table 3.29
Self-Administered Questionnaire (SAQ) Revision (PB)

Before revision	**After revision**
I am concerned about the cost of using the new retail system.	我担心的是使用新零售系统的成本。
I am concerned about the privacy risks of the new retail system.	我担心新零售系统的隐私风险。
I am concerned about the difficulties of using the new retail system.	我担心新零售系统的使用困难。

I am concerned about the reliance of the new retail system on electronic devices.	我担心新零售体系对电子设备的依赖。
I believe I cannot use the new retail system well.	我相信我不能很好地使用新零售系统。

Table 3.30
Self-Administered Questionnaire (SAQ) Revision (PU)

Before revision	**After revision**
In my opinion, the new retail system improves the efficiency of purchasing.	我认为，新零售体系提高了采购效率。
The new retail system improves the quality of services.	我认为，新零售体系提高了服务质量。
I believe the new retail system reduces the risk of the Pandemic.	我相信新零售体系可以降低疫情风险。
The new retail system is effective in meeting demands.	我认为，新零售体系有效满足了需求。

Table 3.31
Self-Administered Questionnaire (SAQ) Revision (Social Influence)

Before revision	**After revision**
My family recommended the new retail system, such as e-commerce assistants, just-in-time retail or self-checkout technology.	我的家人向我推荐了新零售系统，比如电子商务助手、即时零售或自助结账技术。
My friends recommended the new retail system, e-commerce assistants, just-in-time retail or self-checkout technology.	我的朋友向我推荐了新零售系统、电子商务助手、即时零售或自助结账技术。
Using the new retail system is considered an essential skill in my community.	在我的社区，使用新零售系统被认为是必备的基本技能。
People who influenced my decision think I should use e-commerce assistants, just-in-time retail or self-checkout technology.	影响我决定的人认为我应该使用电子商务助手、即时零售或自助结账技术。
People around me believe that e-commerce assistants and just-in-time retail or self-checkout technology are entirely acceptable.	我周围的人认为电子商务助手、即时零售或自助结账技术是完全可以接受的。

Table 3.32
Self-Administered Questionnaire (SAQ) Revision (Movement Restrictions)

Before revision	**After revision**
It's not easy to go to a store and go through the shopping process.	去商店完成所有购物过程并不容易。
I cannot easily access transportation.	我不容易获得交通工具。
Going to the store and returning items requires much time and effort.	对我来说，去商店和拿东西回来需要很多时间和精力。

Table 3.33
Self-Administered Questionnaire (SAQ) Revision (Facilitating Conditions)

Before revision	**After revision**
I can search for 4G (5G) networks at my location and local stores, and there are usually no power outages.	我可以在我所在的位置和当地商店搜索 4G（5G）网络，并且通常不会停电。
I have online banking services that support the new retail system.	我有支持新零售系统的网上银行服务。
The other technologies I use are compatible with online grocery shopping.	我使用的其他技术与在线杂货购物兼容。
The supermarket provides self-checkout machines.	超市设有自助结账机。
There is an ample supply of self-checkout machines in the supermarket.	超市内自助结账机供应充足。
Online supermarkets are equipped with intelligent e-commerce assistants.	网上超市配备了电商智能助手。

Table 3.34
Self-Administered Questionnaire (SAQ) Revision (Intention to Use)

Before revision	**After revision**
I am willing to use online supermarkets as an alternative to in-person shopping.	我愿意使用网上超市作为购物行为的替代
Compared to traditional in-person shopping, I prefer online supermarkets.	相比于传统的面对面购物，我更倾向于网上超市

Table 3.35
Self-Administered Questionnaire (SAQ) Revision (Intention to Use)

Before revision	**After revision**
I am willing to use an intelligent e-commerce assistant to communicate and negotiate with stores.	我愿意使用电子商务智能助手与店铺沟通并协商
Compared to face-to-face communication, I prefer communicating and negotiating with the intelligent e-commerce assistant.	相比于面对面沟通，我更倾向于电子商务智能助手沟通和协商

Table 3.36
Self-Administered Questionnaire (SAQ) Revision (Intention to Use)

Before revision	**After revision**
I am willing to use self-checkout systems.	我愿意使用自助结账系统
Compared to traditional waiting in line for a cashier, I prefer self-checkout systems.	相比于传统的排队等待服务员结账，我更倾向于自助结账系统

Table 3.37
Self-Administered Questionnaire (SAQ) Revision (Experience)

Before revision	**After revision**
I have experience using online supermarkets, e-commerce intelligent assistants and self-checkout systems.	我有使用网上超市、电商智能助手、自助结账系统的经验。
I have tried these techniques before.	我以前尝试过这些技术。
I will never forget how to use them.	我永远不会忘记如何使用它们。

Table 3.38
Self-Administered Questionnaire (SAQ) Revision (Using Behaviour)

Before revision	**After revision**
I frequently use online supermarkets.	我经常使用网上超市
I will continue to use online supermarkets.	我会继续使用网上超市

Table 3.39
Self-Administered Questionnaire (SAQ) Revision (Using Behaviour)

Before revision	**After revision**
I frequently use e-commerce intelligent assistants.	我经常使用电子商务智能助手
I will continue to use e-commerce intelligent assistants.	我会继续使用电子商务智能助手

Table 3.40
Self-Administered Questionnaire (SAQ) Revision (Using Behaviour)

Before revision	**After revision**
I frequently use self-checkout systems.	我经常使用自助结账系统
I will continue to use self-checkout systems.	我会继续使用自助结账系统

3.11 Data Saving and Deletion

Data from 150 electronic questionnaires were stored in the Questionnaire Star, while paper questionnaires were kept at the researchers' homes. Afterwards, all the data was saved in Excel. The data from the questionnaires is used solely for this research and does not involve applications outside of this study. The questionnaire will not be maliciously distributed on the Internet. Once the data analysis was complete, the questionnaires were destroyed.

3.12 Test of Survey Bias

Survey bias, also known as response bias, refers to respondents' tendency to answer inaccurately. One cause of survey bias is poorly designed surveys. Tests for survey bias include data screening and reliability testing. Data screening ensures data accuracy before analysis with SPSS software. Additionally, a reliability test assesses the accuracy and consistency of questions for each variable to ensure reliable data

collection. Besides initial reliability and validity analyses of 40 respondents, the reliability and validity of 400 valid questionnaires were also considered as evidence to verify the reasonableness of the research questionnaire. The study also examined sample size, the definition of valid questionnaires, and the rationale behind the questionnaire collection process to minimise bias.

3.12.1 Delete Invalid Questionnaires

In this study, incomplete questionnaires were discarded, as were those filled out in less than three minutes, questionnaires with identical question options, and those containing significant logical contradictions. Respondents' attitudes influence the authenticity of their questionnaire responses, which can easily lead to inaccurate research outcomes. Filling out the questionnaire in under three minutes suggests that respondents did not carefully read or understand all the declarative questions, nor did they reflect sufficiently on how well their answers matched their personal characteristics. Responses to questionnaires with logical contradictions are typically caused by respondents not thoroughly reviewing the questions.

3.12.2 Ensure The Number of Remaining Questionnaires

After deleting invalid questionnaires, the researchers gathered secondary data to supplement the number of questionnaires until 400 were eligible for retention.

3.12.3 Help Respondents Understand the Questionnaire

This study involved both Generation Y and baby boomers. Some older groups may experience dyslexia and comprehension difficulties. The researchers assist older adults who need help understanding the questionnaire's content. Additionally, they prevented the use of misleading words to influence responses in the questionnaire.

3.13 Plan for Data Analysis

Once the questionnaire was pilot-evaluated, revised, and approved by the researcher's supervisor, data collection commenced. The questionnaire was distributed to the targeted population. A cover letter was attached to explain the purpose of filling out the research questionnaire and to assure respondents of confidentiality. The survey questionnaire was sent to 400 people residing in Shanghai, as some incomplete questionnaires might be returned. The data used in this research are based on the questionnaires that respondents answered voluntarily. The online questionnaires were collected via email or hyperlink, while the physical questionnaires were collected using an offline survey approach. The research planned for this survey to take four weeks to complete, during which all answered questionnaires would be collected. Subsequently, the researcher proceeded with data entry. All collected data was screened using a data quality procedure before being analysed with SPSS software.

All data from the returned questionnaire are retrieved and transferred to SPSS for further analysis. Several analyses are conducted to examine the collected data, including descriptive analysis, normality test, reliability test, Pearson correlation analysis, and multiple regression analysis. These analyses are described in the following context.

3.13.1 Data Screening

According to Tabachinick and Fidell (2007), data screening is a procedure to measure data entry accuracy to prevent distorting correlation. Hence, data screening is performed to detect missing values and assess outliers. Furthermore, data screening can be conducted through skewness or kurtosis, square root transformations, inverse transformations, or logarithms using SPSS software.

3.13.2 Descriptive Analysis

Descriptive analysis calculates the mean, standard deviation, and variance of the collected data. The means and standard deviations of each variable item offer a summary of each data category. Additionally, an analysis of variance test was performed to examine differences in respondents' perceptions of new retail adoption. Therefore, the results of the descriptive analysis determine the central tendency and clarify the relationships among variables and findings. Descriptive statistics condense the situation analysis into valuable data, which are then presented as a frequency distribution. The frequency distribution illustrates and describes the demographic characteristics of respondents, such as gender, age, education level, and income.

3.13.3 Normality Test

The following analysis of descriptive analysis is the normality test. A normality test evaluates how a data set graphically presents a good normal distribution. This test examines the data by assessing univariate and multivariate normality to ensure the proper estimation techniques are employed for this study. Furthermore, Saunders et al. (2009) stated that the frequency presented by descriptive analysis can be used to develop histograms and help assess the normality.

3.13.4 Measurement model evaluation

This study employed the structural equation modelling software SmartPLS 4.0 to assess the measurement model, concentrating on indicators of reliability and convergent validity, including Cronbach's α, combined reliability (rho_a), composite reliability (rho_c), average variance extracted (AVE), heterogeneous-homogeneous correlation ratio (HTMT), Fornell-Larcker criterion, and variance inflation factor

(VIF). Among these, Cronbach's α, rho_a, and rho_c measure internal consistency reliability; AVE tests convergent validity; HTMT and the Fornell-Larcker criterion evaluate discriminant validity; and VIF analyses multicollinearity (Hanif, 2023; Dirgiatmo, 2023).

According to the standards proposed by Hair et al. (2010), the minimum acceptable values of Cronbach's α, rho_a, and rho_c are 0.6; the minimum threshold for AVE is 0.5; the maximum permissible HTMT is 0.85; and VIF values should range between 1 and 10 to prevent serious collinearity. The Fornell-Larcker criterion states that the square root of AVE for each latent variable should exceed its highest correlation with other variables to ensure good discriminant validity. The closer the HTMT value is to 1, the lower the discrimination between the two latent variables. Consequently, this study strictly maintains it below 0.85. By systematically testing these indicators, this study verifies the reliability, convergent validity, and discriminant validity of the measurement model, establishing a foundation for subsequent structural model analysis.

3.13.5 Correlation analysis and hypothesis testing

To further validate the relationship between variables and the hypothesis, this study employs the Pearson correlation coefficient to assess the linear correlation between variables. According to Cohen et al. (2009), when the correlation coefficient between two variables exceeds 0.2, it can be preliminarily concluded that there is a certain correlation between them, meaning the former has explanatory power for the latter or may be influenced by it.

In the structural equation model (SEM), path analysis is considered an expanded form of multiple regression analysis, used to assess the causal relationships among direct, indirect, and total paths between variables (Garson, 2013). This study employed SmartPLS to examine the path coefficients between the latent variables and used external loadings to determine the contribution of observed variables to the latent constructs. As suggested by Hulland (1999), the path loading value should exceed 0.7 to indicate that the indicator has good convergent validity.

Furthermore, model fit is also a crucial aspect of this study's evaluation. By assessing the SRMR (standardized residual root mean square), d_ULS (least square difference), d_G (geographic distance residual), chi-square statistic, and NFI (normed fit index) of the saturated and estimated models, this study confirmed that the overall fit is good and supports the alignment between the theoretical hypothesis model and the actual data (Usakli & Rasoolimanesh, 2023). The above test results provide statistical support for the path relationship analysis and hypothesis verification of this study.

3.13.6 Structural model evaluation and Bootstrapping test

After the measurement model passed the reliability, convergent validity, and discriminant validity verification, this study further proceeded to evaluate the structural model. The evaluation mainly focuses on the significance of the path coefficient, the model's fit, and the explanatory power of the relationship between the latent variables. The path coefficient measures the strength and direction of the direct impact of the independent variable on the dependent variable, and its statistical significance must be tested using the non-parametric resampling technique-Bootstrapping. As a widely used method for confidence interval estimation and

significance testing, Bootstrapping is commonly employed in the analysis of structural equation models with relatively small sample sizes (Hair et al., 2017).

This study employed SmartPLS 4.0 to conduct 5000 bootstrap samples and calculated the standard error, T value, P value, and confidence interval. If the T value of the path coefficient exceeds 1.96 (at the significance level $\alpha = 0.05$) and the P value is below 0.05, it indicates that the path relationship is statistically significant. To also consider the strength of the path effect, this study incorporates the standardised path coefficient (β) in the interpretation. A β value above 0.2 suggests a moderate effect, while a value above 0.3 indicates a strong effect (Cohen, 1988).

In the multiple relationship test, this study also further evaluated the model's coefficient of determination (R^2), predictive relevance (Q^2), and effect size (f^2). The R^2 value indicates how much the independent variable can explain the variation of the dependent variable. The Q^2 value is derived using the Blindfolding procedure to assess the model's predictive effectiveness. The f^2 value measures the explanatory power of a single path. Hair et al. (2010) noted that R^2 values greater than 0.26 indicate strong explanatory power, Q^2 values above 0 suggest the model has predictive relevance, and f^2 values of 0.02, 0.15, and 0.35 represent small, medium, and large effect sizes, respectively.

Based on the above evaluation results, if the model's significance, explanatory power, and predictive capacity indicators all meet the standards, it indicates that the structural model is established and the proposed hypothesis has both theoretical and statistical support.

3.14 Chapter Summary

This chapter outlines the research methodology and design employed to achieve the study's objectives. The self-administered survey questionnaire was used to gather data from the targeted population. The results, analysed using SmartPLS software, are discussed in the next chapter.

CHAPTER FOUR

DATA ANALYSIS

4.1 Introduction

In Chapter 4, data analysis was carried out, as detailed below. This chapter repeats the reliability analysis, Bartlett's test, and KMO analysis, as they should be based on 400 data points, not just 40, as in Chapter Three. The research findings are presented in the latter part of this chapter (Smart PLS analysis in Appendix C and D).

4.2 Data Screening

Data screening is a crucial stage in the data analysis process. This vital step involves a series of careful checks and assessments to improve the dataset's quality and dependability before moving on to more advanced analyses. As Pallant (2011) outlined, data screening generally includes reviewing key aspects such as identifying missing values, spotting outliers and extreme data points, and examining survey respondents who may have hurried through the questionnaire.

4.2.1 Speed

This study encompasses over 50 psychological and personal questions. Therefore, individuals who complete the questionnaire in under 60 seconds are considered participants who may not have given the questions adequate thought. Consequently, their data outcomes could lack accuracy

Table 4.1
Writing Speed

	Speed	N
Gen Y	<60 s	20
	>60 s	200
Baby boomer	<60 s	1
	>60 s	199

After this phase, the study retained 399 data sets, with 200 from the Generation Y group and 199 from the Baby Boomer group, while excluding 21 data sets.

4.2.2 Completeness

It is important to note that not every participant in the remaining dataset completed the questionnaire; some stopped participating during the process. As a result, questionnaires that were unfinished were excluded from the analysis. This aligns with the methodology proposed by Tabachnick and Fidell (2007), who recommend removing questionnaires with missing values immediately before entering data into statistical software.

Table 4.2
Writing Completeness

	Completeness	N
Gen Y	<100 %	0
	100 %	200
Baby boomer	<100 %	0
	100 %	199

In this phase, no data was removed because all questions in the electronic questionnaires were mandatory. However, participants could exit the electronic questionnaire if they chose not to continue, and their responses were not recorded. For

paper-based questionnaires, researchers assisted elderly participants in completing them. Furthermore, the questionnaire did not contain any ethically objectionable content, so there were no barriers to completing it in its entirety. Of course, researchers allowed elderly individuals who did not wish to answer specific questions to skip them.

4.2.3 Outliers and Extreme Values

4.2.3.1 Box Plots

Box plots are a standard method for checking outliers; they can display values that are significantly different from other questionnaires (McCormick & Salcedo, 2017). This study analysed the questionnaires completed by respondents, aiming to identify and remove outliers from the dataset. During the detection process using box plots, researchers did not find any outliers or extreme values (Figure 4.1). Consequently, the data can proceed to the next stage of analysis (Table 4.3).

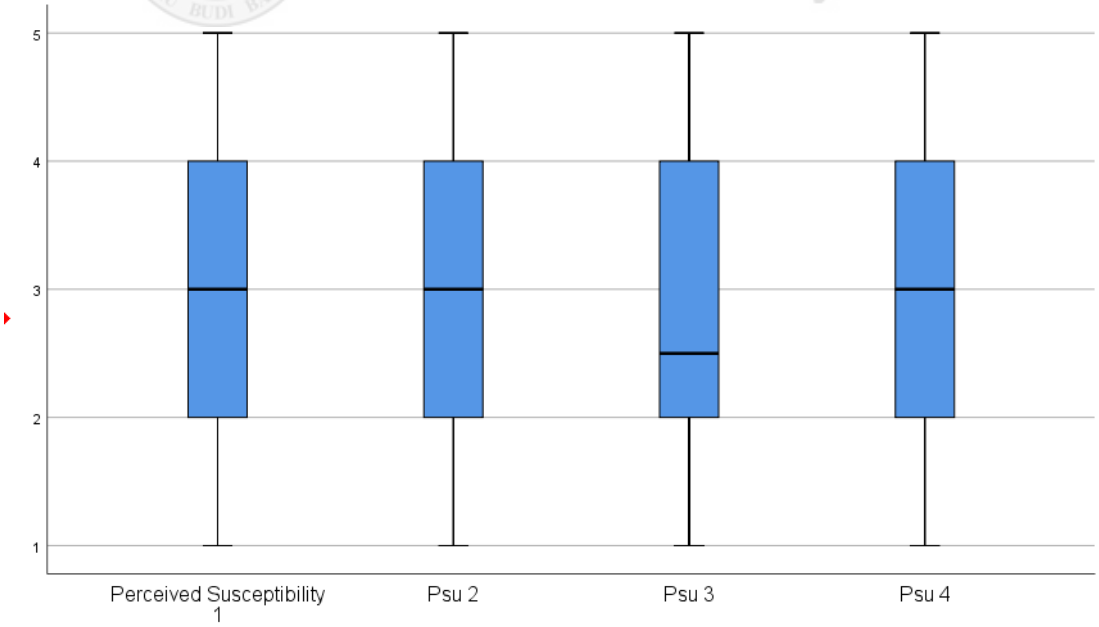


Figure 4.1 Box Plots

Table 4.3
Box Plots Result

	Outliers or extreme values	Remaining N
Gen Y	0	200
Baby boomer	0	199

4.2.3.2 Z-scores

In addition to box plots, Z-scores are also a method used to identify outliers in data. Z-scores show how far each data point in a dataset deviates from the overall mean (Seo, 2006). Researchers can use this approach to spot outliers and extreme values. Generally, in smaller data sets (fewer than 80), data points with an absolute deviation from the mean exceeding 2.5 are considered undesirable (Hair et al., 2010). In larger data sets (80 or more), data points with an absolute deviation from the mean exceeding four are considered undesirable (Hair et al., 2010).

In this study, the total sample size is 399. Therefore, researchers considered data points with deviations smaller than four as acceptable. After screening, all samples met the research requirements (Figure 4.2). Consequently, the remaining total sample size is 399.

ZSco01	ZPsu2	ZPsu3	ZPsu4	ZPerceivedSeverity1	ZPse2	ZPse3	ZPse4	ZPse5
.67566	1.66102	.92410	.21866	.36512	-.35079	-.36467	.52605	-.42643
-.05086	.06772	.16038	.21866	.36512	.46500	1.31198	.52605	-.42643
.67566	.86437	1.68782	1.02851	.36512	-.35079	-.36467	.52605	1.21367
-.05086	.06772	-.60334	.21866	.36512	1.28078	1.31198	1.38844	-.42643
1.40217	1.66102	1.68782	1.02851	1.12580	1.28078	1.31198	1.38844	-.42643
-.05086	.06772	.16038	.21866	.36512	-.35079	-.36467	.52605	.39362
-.05086	.06772	.16038	.21866	1.12580	.46500	1.31198	1.38844	1.21367
1.40217	.86437	.92410	1.83836	1.12580	-.35079	1.31198	1.38844	-.42643
.67566	1.66102	1.68782	1.83836	-.39555	.46500	-.36467	1.38844	.39362
-1.50389	-1.52559	-1.36706	-1.40104	1.12580	.46500	-.36467	-.33633	-.42643
-.77737	-1.52559	-1.36706	-1.40104	1.12580	.46500	-.36467	-.33633	1.21367
1.40217	.86437	1.68782	1.02851	.36512	-.35079	1.31198	.52605	1.21367
-1.50389	-.72894	-.60334	-1.40104	-.39555	.46500	-.36467	-.33633	-.42643
1.40217	1.66102	1.68782	1.83836	1.12580	.46500	1.31198	-.33633	1.21367
-1.50389	-1.52559	-1.36706	-1.40104	-.39555	1.28078	-.36467	-.33633	1.21367
-.77737	.06772	.16038	-.59119	1.12580	-.35079	1.31198	.52605	.39362
.67566	1.66102	.16038	1.02851	1.12580	1.28078	-.36467	1.38844	-.42643
-.05086	.86437	.16038	-.59119	1.12580	1.28078	1.31198	1.38844	1.21367
.67566	.86437	1.68782	1.02851	.36512	-.35079	1.31198	.52605	.39362
1.40217	1.66102	1.68782	1.83836	-.39555	.46500	.47366	-.33633	1.21367
-.77737	-.72894	-.60334	.21866	.36512	-.35079	-.36467	-.33633	-.42643
-.77737	-.72894	-1.36706	-1.40104	1.12580	-.35079	-.36467	.52605	-.42643
-.05086	.06772	-.60334	.21866	.36512	.46500	-.36467	-.33633	-.42643
1.40217	1.66102	.92410	1.02851	-.39555	-.35079	-.36467	.52605	.39362
1.40217	1.66102	1.68782	1.02851	1.12580	-.35079	.47366	-.33633	1.21367
1.40217	.86437	1.68782	1.83836	1.12580	1.28078	1.31198	-.33633	1.21367
-.05086	.06772	-.60334	-.59119	-.39555	1.28078	.47366	1.38844	1.21367
-1.50389	-1.52559	-.60334	-1.40104	1.12580	.46500	-.36467	1.38844	.39362

Figure 4.2 Z-scores

Table 4.4
Z-scores Result

	Outliers or extreme values	Remaining N
Gen Y	0	200
Baby boomer	0	199

4.3 Survey Response

Analysing the collected survey responses allows the researcher to identify and implement necessary actions based on the completed questionnaires (Ranjit, 2011). Previous researchers have emphasised that analysing the gathered responses from the field helps to identify the main themes of the study (Mamdouh, 2010).

This study analysed the returned questionnaires using IBM SPSS version 22. The software helped assess the response rate, test for non-response bias, and generate descriptive statistics of the respondents.

4.3.1 Survey Cycle

The survey for this study was conducted from 1st February 2023 to 30th February 2023, in Shanghai, China. Due to the inclusion of the baby boomer and Gen Y populations, data collection took a longer period. All participants completed the questionnaire voluntarily, and it was considered valid once all questions were answered. If some participants refused to answer certain sections, those questionnaires were invalidated.

4.3.2 Survey Response Rate

Table 4.5
Respondent rate

		Frequency	Per cent	Cumulative Percent
Valid	Gen Y	200	50.12	50.12
	Baby boomer	199	49.88	100

The paper-based questionnaires in this study were distributed and completed with the researchers' assistance. As a result, the number of questionnaires distributed was equal to the number collected. According to Hair et al. (2010), a response rate exceeding 30% is deemed reasonable. The response rate for this study was 99.75%, which is outstanding.

4.3.3 Non-Response Bias Test

In the research field, one common issue is whether responses from respondents who decline to participate align with those who agree. Some researchers have noted that the rules for questionnaire completion among those who decline may not always be consistent with those who participate (Af Wåhlberg & Poom, 2015). In this regard, after obtaining the full sample size, this study requested the participation of 20 individuals from Generation Y and 20 individuals from the baby boomer generation. Although this request was unreasonable and unethical, researchers gave each participant a financial compensation of 20 RMB as a token of appreciation. However, it is unfair to those who completed the questionnaire without compensation. The study must acknowledge that achieving absolute fairness is challenging, especially with limited funds.

The research results show no significant difference between respondents and non-respondents. Although there is considerable variation in perceived financial costs (Gen

Y) (Table 4.6), it does not influence the overall attitude of the questionnaire respondents.

Table 4.6
Descriptive Statistics (Gen Y)

	N	Mean	Std. Deviation	Attitude
PSU (Responders)	200	2.8763	1.18194	Uncertain
PSU (non-responders)	20	2.9225	.88846	Uncertain
DE (Responders)	200	4.5125	.20798	Strongly agree
DE (non-responders)	20	4.2253	.39751	Strongly agree
PFC (Responders)	200	3.2125	1.25758	Uncertain
PFC (non-responders)	20	2.6878	.98654	Uncertain
PR (Responders)	200	3.3800	1.07665	Uncertain
PR (non-responders)	20	3.0879	.87124	Uncertain
PS (Responders)	200	4.4792	.18825	Strongly agree
PS (non-responders)	20	4.2346	.33524	Strongly agree
PB (Responders)	200	1.9890	.47835	Disagree
PB (non-responders)	20	1.8017	.64785	Disagree
PU (Responders)	200	4.4638	.25112	Strongly agree
PU (non-responders)	20	4.2142	.42512	Strongly agree
SI (Responders)	200	3.4680	.90480	Agree
SI (non-responders)	20	3.7852	.77415	Agree
MR (Responders)	200	2.3767	1.03663	Disagree
MR (non-responders)	20	2.0114	.79845	Disagree

4.4 Demographic Profile

4.4.1 Gender

Table 4.7
Gender (Gen Y)

		Frequency	Per cent	Valid Percent	Cumulative Percent
Valid	Female	117	58.5	58.5	58.5
	Male	83	41.5	41.5	100.0

	Total	200	100.0	100.0	

In China, there were more female respondents in the study. In Chinese society, women are more actively involved in family responsibilities such as cooking, purchasing household goods, and other types of housework (Luo & Chui, 2019). This gender distribution is gradually changing with urbanisation, although the change is happening slowly.

Table 4.8
Gender (Baby Boomer)

		Frequency	Per cent	Valid Percent	Cumulative Percent
Valid	Female	99	49.7	49.7	49.7
	Male	100	50.3	50.3	100.0
	Total	199	100.0	100.0	

The questionnaires for the Chinese elderly participants were administered face-to-face. The researchers made reasonable efforts to control the gender distribution of the participants to achieve a better balance. As a result, the proportion of male and female respondents in the study was relatively similar.

4.4.2 Group

Table 4.9
Group (Gen Y)

		Frequency	Per cent	Valid Percent	Cumulative Percent
Valid	Gen Y	200	100.0	100.0	100.0
	Baby boomer	199	100.0	100.0	100.0

To ensure a meaningful comparison between Generation Y and the Baby Boomer generation, the sample sizes of both groups were carefully adjusted for similarity in this study. For example, there were 200 members of Generation Y and 199 members of the Baby Boomer generation. This approach was adopted to minimise the influence of extraneous variables on the comparison between the two groups.

4.4.3 Education

Table 4.10
Education (Gen Y)

		Frequency	Per cent	Valid Percent	Cumulative Percent
Valid	High school and below	44	22.0	22.0	22.0
	Undergraduate	119	59.5	59.5	81.5
	Postgraduate	37	18.5	18.5	100.0
	Total	200	100.0	100.0	

Members of Generation Y in China are generally well educated, with a large proportion holding a bachelor's degree. When considering the educational achievement of Generation Y, there is an even split between those with graduate qualifications and those with only a high school education. China is currently experiencing an educational shift, with more people gaining access to higher education and a government emphasis on lifelong learning (Chen, 2023).

Table 4.11
Education (Baby Boomer)

		Frequency	Per cent	Valid Percent	Cumulative Percent
Valid	Undergraduate and above	50	25.1	25.1	25.1
	High school	44	22.1	22.1	47.2
	Junior high school and below	105	52.8	52.8	100.0
	Total	199	100.0	100.0	

In the past, China lacked a strong educational environment, and people did not emphasise the significance of education for personal growth. As a result, older adults generally did not pursue higher education and often only completed junior high or elementary school. As some studies have shown, China faced deficiencies in education in the past (Yang, 2022). However, with the passage of time and a push for educational reform, there have been notable improvements in the educational environment and attainment. Modern China increasingly recognises the importance of education and continues to strive to improve its quality and accessibility.

4.4.4 Living Condition

Table 4.12
Marital status (Gen Y)

		Frequency	Per cent	Valid Percent	Cumulative Percent
Valid	Single	87	43.5	43.5	43.5
	Married	113	56.5	56.5	100.0
	Total	200	100.0	100.0	

Among the surveyed Gen Y participants in China, there is a slightly higher proportion of married individuals than unmarried ones. This reflects one of the major issues

currently faced in China: people are increasingly hesitant to marry and tend to delay marriage (Gui, 2020). This trend can be linked to various factors, such as changing societal norms, economic considerations, and personal and career development choices. The shift in attitudes towards marriage has significant implications for social dynamics and family structures in China.

Table 4.13
Lifestyle (Baby Boomer)

		Frequency	Per cent	Valid Percent	Cumulative Percent
Valid	Alone	68	34.2	34.2	34.2
	With children	75	37.7	37.7	71.9
	Nursemaid	56	28.1	28.1	100.0
	Total	199	100.0	100.0	

In the case of older adults, this study considers it impolite to ask about their marital status. Therefore, the focus among older adults is on whether they live alone, live with their children, or have a caregiver and companion. The results show that these three groups are relatively similar in proportion.

This finding indicates that older adults in China have a variety of living arrangements, with some living independently, some residing with their adult children, and others receiving support from caregivers. Various factors, including cultural norms, personal circumstances, and the availability of support networks, shape older adults' preferences and situations regarding their living arrangements.

4.4.5 Descriptive Statistics for Variables

Nyutu et al. (2021) provided rating details on a 5-point Likert scale originally adapted from Pimentel (2010). Based on this information, the current study conducted an initial descriptive analysis of the data's statistical results.

Likert-Scale Description	Likert-Scale	Likert Scale interval
Strongly disagree	1	1.00 - 1.80
Disagree	2	1.81 - 2.60
Neutral/Uncertain	3	2.61 - 3.40
Agree	4	3.41 - 4.20
Strongly agree	5	4.21 - 5.00

Figure 4.3 5-Likert Scales Description by Nyutu et al. (2021)

4.4.5.1 Variable Descriptive of Gen Y

In China, Gen Y has become less concerned about the dangers and effects of the pandemic. However, they highly value digital devices, perceive high self-efficacy, recognise the usefulness of technology, and have a positive attitude towards their experiences with digital technology. Interestingly, they prefer self-checkout systems and show a strong intention to use them, but they have a weaker intention to use e-commerce intelligent assistants. Most Gen Y individuals believe there are no mobility restrictions and are able to go out and shop without any issues.

Table 4.14
Descriptive Statistics (Gen Y)

	N	Mean	Std. Deviation	Attitude
PSU (Perceived Susceptibility)	200	2.8763	1.18194	Uncertain
DE (Digital Equipment)	200	4.5125	.20798	Strongly agree
PFC (Perceived Financial Cost)	200	3.2125	1.25758	Uncertain
PR (Privacy Risk)	200	3.3800	1.07665	Uncertain

PS (Perceived Self-Efficacy)	200	4.4792	.18825	Strongly agree
PB (Perceived Barriers)	200	1.9890	.47835	Disagree
PU (Perceived Usefulness)	200	4.4638	.25112	Strongly agree
SI (Social Influence)	200	3.4680	.90480	Agree
MR (Movement Restrictions)	200	2.3767	1.03663	Disagree
FC (Facilitating Conditions)	200	3.9938	.40291	Agree
ITUA (Intention to Use of Instant Retail)	200	3.9750	.61951	Agree
ITUB (Intention to Use of E-Commerce Assistant)	200	2.0250	.58402	Disagree
ITUC (Intention to Use of Self-Checkout System)	200	4.4375	.33974	Strongly agree
EXP (Experience)	200	4.4567	.30133	Strongly agree
UBA (Using Behavior of Instant Retail)	200	3.9975	.60046	Agree
UBB (Using Behavior of E-Commerce Assistant)	200	2.0100	.53977	Disagree
UBC (Using Behavior of Self-Checkout System)	200	3.9700	.58807	Agree
PSE (Perceived Severity)	200	3.4590	.97914	Agree
PHB (Perceived Health Benefits)	200	3.1360	1.05139	Uncertain
Valid N (listwise)	200			

4.4.5.2 Variable Descriptive of Baby Boomer

In China, older adults are often encouraged by their family members or friends to use new retail systems. They do not fear the Pandemic or see it as highly contagious. However, they still believe that the Pandemic may worsen their existing health conditions and potentially lead to their demise.

They are not keen on engaging with e-commerce intelligent assistants. This might be because they are not skilled at typing or organising information logically.

Table 4.15
Descriptive Statistics (Baby Boomer)

	N	Mean	Std. Deviation	Attitude
PSU	199	3.1106	1.32587	Uncertain
ITUA	199	3.4497	1.42045	Agree
PSE	199	4.1839	.69757	Agree
DE	199	3.4615	1.37209	Agree
PHB	199	2.0271	.97870	Disagree
PFC	199	3.0075	1.40524	Uncertain
PR	199	2.5477	1.34448	Disagree
PS	199	3.4188	1.38604	Agree
PB	199	2.5558	1.37086	Disagree
PU	199	3.4296	1.41134	Agree
SI	199	4.2452	.75329	Strongly agree
MR	199	3.4673	1.37923	Agree
FC	199	4.0515	.94457	Agree
ITUB	199	2.0905	1.14784	Disagree
ITUC	199	3.4372	1.34458	Agree
Experience	199	3.4255	1.40062	Agree
SR	199	1.7977	.84588	Strongly disagree
UBA	199	3.4171	1.39874	Agree
UBB	199	2.1080	1.17514	Disagree
UBC	199	3.4196	1.40654	Agree
Valid N (listwise)	199			

4.5 Normality Test

4.5.1 Skewness And Kurtosis Test

In parametric testing, the assumption depends on the normality of the data. Therefore, it is essential to evaluate whether the data are normally distributed. This assessment helps determine if the data are symmetrically spread. A perfectly normal distribution shows skewness and kurtosis values of zero. Positive skewness indicates a right tail, whereas negative skewness indicates a left tail. Similarly, a positive kurtosis value

signifies a peaked or leptokurtic distribution, while a negative kurtosis indicates a flatter or platykurtic distribution (Coakes, 2013).

The acceptable range for skewness and kurtosis values is within ±1.96. Specifically, the normality assumption is questioned when the test value falls outside this range at a significance level of P<0.05. This range extends to ±2.56 at P<0.001 when the sample size exceeds 200. With our sample size of 199 (baby boomer) and 200 (Gen Y) participants, the acceptable absolute values for scores are within ±1.96 for P<0.05 (Ghasemi & Zahediasl, 2012; Rose, Spinks & Canhoto, 2015). Table 4.16 demonstrates that all scores are within the ±1.96 criterion and are significant at P<0.05, indicating a normal data distribution.

Table 4.16
Skewness and Kurtosis Test

	N	Skewness		Kurtosis	
	Statistic	Statistic	Std. Error	Statistic	Std. Error
PSU	200	.151	.172	-1.234	.342
PSE	200	-.771	.172	-.749	.342
PHB	200	.388	.172	-1.183	.342
DE	200	-.033	.172	-.268	.342
PFC	200	-.484	.172	-1.237	.342
PR	200	-.463	.172	-1.090	.342
PS	200	-.068	.172	-.175	.342
PB	200	.001	.172	-1.245	.342
PU	200	-.005	.172	-.548	.342
SI	200	-1.378	.172	1.080	.342
MR	200	1.267	.172	.443	.342
FC	200	-.054	.172	-.563	.342
Experience	200	.147	.172	-.742	.342
SR	200	-.074	.172	-.726	.342
ITU	200	.160	.172	-1.039	.342
WEB	200	.080	.172	-.955	.342
Valid N (listwise)	200				

4.5.2 P-P Plot and Q-Q Plots

P-P Plot and Q-Q Plot are two closely related charts commonly used to test the normality of data (Das & Imon, 2016). The similarity between these two test methods lies in identifying whether the points on the graph are evenly distributed along the diagonal line. Therefore, this study combines both plots to describe the data. The research results indicate that all data points are evenly distributed around the diagonal line, conforming to the characteristics of a normal distribution.

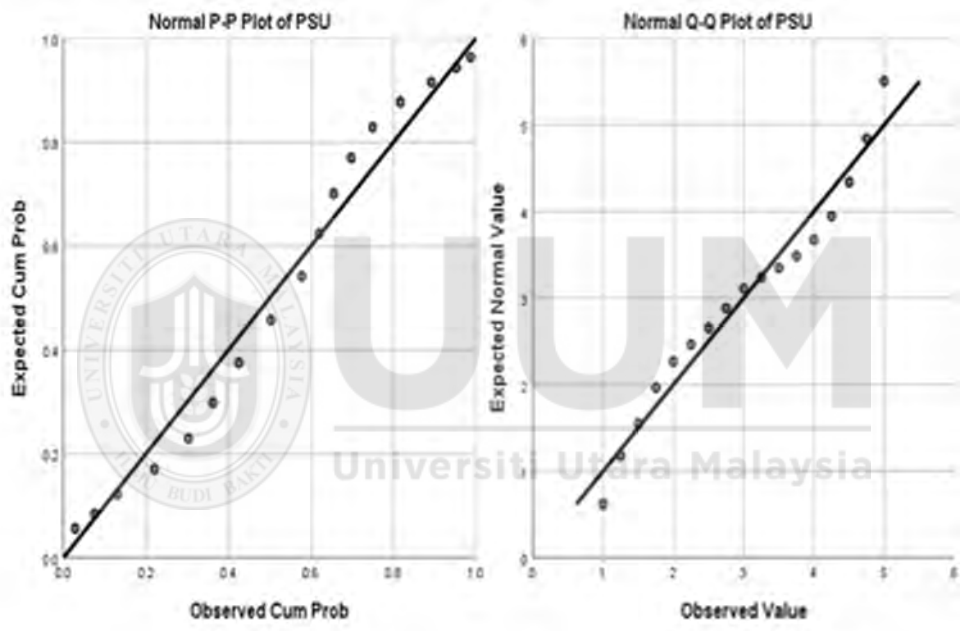


Figure 4.4 P-P Plot and Q-Q Plots

4.6 Reliability and Validity Testing

4.6.1 Baby boomers

Table 4.17
Cronbach's alpha and AVE (Baby boomers)

	Cronbach's alpha	rho_a	rho_c	AVE
DE	0.982	0.982	0.985	0.816
EC	0.909	0.931	0.937	0.789

Experience	0.965	0.965	0.977	0.834
Intention	0.785	0.756	0.715	0.662
MR	0.965	0.965	0.977	0.834
PB	0.977	0.977	0.982	0.717
PFC	0.973	0.975	0.980	0.826
PHB	0.959	0.970	0.968	0.859
PR	0.980	0.980	0.984	0.811
PS	0.976	0.901	0.982	0.731
PSe	0.924	0.965	0.917	0.690
PSef	0.981	0.981	0.985	0.915
PU	0.973	0.973	0.980	0.926
SI	0.922	0.924	0.941	0.761
UB	0.780	0.749	0.712	0.655

This study refers to the recommendations of Hair et al. (2019) and Taber (2018) and is implemented in combination with the standard norms of structural equation modeling. Cronbach's Alpha, Composite Reliability (ρ_a and $\rho\mathcal{C}$), and Average Variance Extracted (AVE) were used to evaluate the measurement model.

4.6.1.1 Internal Consistency Reliability

Cronbach's Alpha and Composite Reliability (ρ_a and $\rho\mathcal{C}$) are critical metrics for evaluating the internal consistency of a construct, which determines whether multiple observed indicators effectively measure the same latent variable. Generally, values exceeding 0.70 indicate acceptable reliability, while values above 0.90 demonstrate excellent internal consistency (Hair et al., 2019; Taber, 2018).

In this study, all constructs surpassed the 0.70 threshold, confirming satisfactory reliability. Notably, constructs such as Perceived Usefulness (PU) (Cronbach's α = 0.973, ρ_a = 0.973, $\rho\mathcal{C}$ = 0.980), Perceived Self-Efficacy (PSef) (α = 0.981, ρ_a = 0.981, $\rho\mathcal{C}$ = 0.985), and Device Empowerment (DE) (α = 0.982, ρ_a = 0.982, $\rho\mathcal{C}$ = 0.985)

exhibited extremely high reliability, demonstrating strong internal consistency and robust scale construction.

Even constructs with lower coefficients, such as Usage Behavior (UB) ($\alpha = 0.780$, $\rho_a = 0.749$, $\rho\mathcal{C} = 0.712$) and Intention to Use (Intention) ($\alpha = 0.785$, $\rho_a = 0.756$, $\rho\mathcal{C} = 0.715$), still met the minimum recommended thresholds, thereby indicating sufficient internal coherence for research purposes.

4.6.1.2 Convergent Validity

Convergent validity refers to the degree to which multiple indicators of a construct are related and measure the same concept. This is typically assessed using the Average Variance Extracted (AVE), with values exceeding 0.50 considered acceptable (Fornell & Larcker, 1981; Hair et al., 2019).

All constructs in this study demonstrated satisfactory convergent validity, with AVE values ranging from 0.655 to 0.926. Constructs such as Perceived Usefulness (PU) (AVE = 0.926), Perceived Self-Efficacy (PSef) (AVE = 0.915), and Protective Health Behavior (PHB) (AVE = 0.859) performed exceptionally well, reflecting a high proportion of shared variance among their respective items.

Although Usage Behavior (UB) (AVE = 0.655) and Intention to Use (Intention) (AVE = 0.662) showed relatively lower AVE values compared to other constructs, both exceeded the 0.50 threshold, indicating acceptable convergent validity. These results confirm that the majority of variance in their respective items is explained by the latent construct, thus supporting construct validity.

4.6.1.3 Discriminant validity analysis of HTMT

Table 4.18
HTMT (Baby boomers)

	DE	EC	Ex	UI	MR	PB	PFC	PHB	PR	PS	PSe	PSef	PU	SI	UB
DE															
EC	0.457														
Ex	0.727	0.314													
UI	0.659	0.464	0.751												
MR	0.667	0.481	0.721	0.562											
PB	0.696	0.482	0.727	0.652	0.463										
PFC	0.469	0.295	0.361	0.443	0.441	0.483									
PHB	0.094	0.09	0.052	0.082	0.067	0.1	0.046								
PR	0.591	0.461	0.723	0.555	0.564	0.696	0.463	0.098							
PS	0.042	0.085	0.043	0.072	0.033	0.065	0.068	0.091	0.061						
PSe	0.063	0.085	0.04	0.096	0.057	0.055	0.104	0.349	0.064	0.122					
PSef	0.674	0.465	0.732	0.639	0.548	0.679	0.444	0.084	0.374	0.048	0.045				
PU	0.59	0.482	0.727	0.653	0.664	0.499	0.468	0.096	0.596	0.065	0.051	0.571			
SI	0.393	0.632	0.354	0.411	0.387	0.387	0.3	0.083	0.383	0.177	0.053	0.367	0.406		
UB	0.957	0.444	0.751	0.496	0.547	0.549	0.44	0.088	0.447	0.078	0.077	0.532	0.551	0.405	

In the structural equation model, discriminant validity is used to verify whether there is sufficient theoretical distinction between latent variables. If the measurement items between two latent variables are highly correlated, there may be problems such as construct overlap and questionnaire design confusion. According to the suggestions of Henseler et al. (2015) and Hair et al. (2017), the Heterotrait–Monotrait Ratio of Correlations is ideal as a primary discriminant validity assessment tool. If the HTMT value is less than 0.85, it can be determined that there is good discriminant validity between the variables; if it is between 0.85 and 0.90, it is necessary to make a cautious judgment in combination with theoretical semantics; if it is greater than 0.90, there may be serious construct confusion, and it is not recommended to keep the two variables in the same model.

The HTMT values of Protective Health Behavior (PHB) and all other variables are significantly lower than 0.1, indicating that their measurement contents are

independent. For example, the similarity between PHB and PU (HTMT = 0.096), PB (HTMT = 0.100), and DE (HTMT = 0.094) is extremely low, indicating that the semantic separation between variables is clear. The HTMT between Device Empowerment (DE) and Experience is 0.727, and the HTMT between Perceived Self-Efficacy (PSef) and Experience is 0.732. Although they are at a medium to high level, they do not exceed the critical value and are in line with the theoretical correlation expectations between skilled equipment operation and past experience, so they are acceptable.

4.6.1.4 Discriminant validity analysis of Fornell-Larcker

Table 4.19
Fornell-Larcker (Baby Boomers)

	DE	EC	Ex	UI	MR	PB	PFC	PHB	PR	PS	PSe	PSef	PU	SI	SR	UB
DE	0.957															
EC	0.436	0.888														
Ex	0.707	0.302	0.966													
UI	0.952	0.442	0.716	0.814												
MR	0.941	0.454	0.696	0.938	0.966											
PB	-0.906	-0.458	-0.706	-0.944	-0.935	0.957										
PFC	-0.459	-0.283	-0.351	-0.432	-0.428	0.472	0.962									
PHB	-0.093	0.088	0.046	-0.076	-0.066	0.099	-0.041	0.927								
PR	-0.902	-0.44	-0.703	-0.949	-0.938	0.905	0.453	0.096	0.954							
PS	-0.04	-0.077	0.04	-0.066	-0.034	0.065	0.066	0.088	0.061	0.965						
PSe	0.118	0.144	0.014	0.108	0.095	-0.107	0.009	-0.34	-0.112	0.095	0.831					
PSef	0.956	0.443	0.712	0.931	0.923	-0.959	-0.435	-0.082	-0.956	-0.049	0.093	0.956				
PU	0.967	0.456	0.705	0.944	0.934	-0.974	-0.457	-0.094	-0.973	-0.065	0.098	0.949	0.962			
SI	0.375	0.589	0.334	0.387	0.367	-0.369	-0.287	0.076	-0.366	-0.168	0.063	0.351	0.386	0.872		
SR	0.101	0.245	0.138	0.037	0.051	-0.109	0.047	0.003	-0.097	0.034	-0.013	0.116	0.126	0.346	0.893	
UB	0.95	0.433	0.719	0.973	0.926	-0.943	-0.438	-0.075	-0.942	-0.075	0.096	0.923	0.942	0.378	0.056	0.809

Fornell-Larcker uses the AVE square root of each latent variable as the discriminant basis and places it on the main diagonal of the correlation matrix. If the AVE square root of a variable is greater than the correlation coefficient between it and all other variables, it indicates that the explanatory power of the variable in measurement

mainly comes from its own dimension rather than other constructs, thus meeting the requirements of discriminant validity (Afthanorhan et al., 2021). The AVE square roots of all latent variables are located on the diagonal of the correlation matrix and are significantly greater than their correlation coefficients with other latent variables. For example, the AVE square root of Device Empowerment (DE) is 0.957, while its correlation coefficients with Usage Behavior (UB), Intention and Perceived Usefulness (PU) are 0.950, 0.952 and 0.967 respectively, which are close to but not exceeding the main diagonal value, indicating that there is still sufficient differentiation between constructs. In addition, the square root of AVE of Perceived Self-Efficacy (PSef) is 0.956, which remains separate from its related variables such as intention (0.931) and usage behavior (0.923), indicating that even in a combination of constructs with high theoretical relevance, the questionnaire items can still clearly distinguish the psychological representations of different constructs.

4.6.2 Gen Y

Table 4.20
Cronbach's alpha and AVE (Gen Y)

	Cronbach's alpha	(rho_a)	(rho_c)	(AVE)
DE	0.843	0.873	0.883	0.790
E	0.830	0.808	0.824	0.733
EC	0.923	0.881	0.789	0.657
Intentiontouse	0.882	0.821	0.850	0.720
MR	0.819	0.833	0.892	0.733
PB	0.884	0.783	0.797	0.539
PFC	0.960	0.960	0.971	0.893
PHB	0.911	0.961	0.929	0.723
PR	0.945	0.946	0.957	0.786
PSEF	0.913	0.840	0.828	0.673
PU	0.815	0.795	0.830	0.756
Pse	0.860	0.915	0.893	0.626
Psu	0.933	0.996	0.951	0.828
SI	0.892	0.896	0.920	0.698
SR	0.908	0.873	0.977	0.759

UB	0.861	0.855	0.873	0.527

4.6.2.1 Internal Consistency Reliability

The data of this study show that the reliability of most variables is excellent. For example, the Cronbach's Alpha of Equipment Enablement (DE) is 0.843, rho_a is 0.873, and rho_c is 0.883, which is significantly higher than the standard of 0.7, indicating that this variable has a very high measurement consistency. Other variables such as Perceived Financial Cost (PFC) ($\alpha = 0.960$, $\rho\_c = 0.971$) and Perceived Risk (PR) ($\alpha = 0.945$, $\rho\_c = 0.957$) also show an extremely excellent reliability level.

4.6.2.2 Convergent Validity

According to the standard of Fornell & Larcker (1981), if the AVE is greater than 0.5, it means that the item can explain more than 50% of the construct variance and has good convergent validity. In this study, except for the AVE values of usage behavior (UB) and perceived barriers (PB) which are slightly lower than 0.6 (UB = 0.527, PB = 0.539), the AVE of all other variables are far higher than the standard threshold. For example, the AVE of perceived financial cost (PFC) is as high as 0.893, perceived self-efficacy (PSEF) is 0.673, and perceived susceptibility (PSU) is 0.828, all of which indicate that the measurement items are highly correlated and can effectively focus on the common latent construct. It is worth affirming that in terms of structural construction, the AVE of most latent variables is greater than the 0.7 threshold of their corresponding rho_c, which further confirms the theoretical rationality and empirical validity of the questionnaire design in dimensional division.

4.6.2.3 Discriminant validity analysis of HTMT

Table 4.21
HTMT(Gen Y)

	DE	E	EC	UI	MR	PB	PFC	PHB	PR	PSEF	PU	Pse	Psu	SI	UB
DE															
E	0.671														
EC	0.654	0.601													
UI	0.658	0.597	0.838												
MR	0.401	0.29	0.588	0.45											
PB	0.375	0.779	0.592	0.745	0.603										
PFC	0.264	0.443	0.381	0.698	0.703	0.521									
PHB	0.274	0.362	0.355	0.639	0.503	0.84	0.838								
PR	0.263	0.411	0.401	0.721	0.657	0.406	0.804	0.856							
PSEF	0.643	0.549	0.294	0.589	0.318	0.48	0.309	0.321	0.04						
PU	0.681	0.557	0.828	0.522	0.349	0.345	0.249	0.305	0.264	0.707					
Pse	0.43	0.363	0.486	0.572	0.753	0.68	0.878	0.63	0.83	0.41	0.275				
Psu	0.259	0.416	0.522	0.227	0.118	0.252	0.156	0.111	0.148	0.333	0.229	0.15			
SI	0.289	0.287	0.611	0.49	0.88	0.662	0.729	0.588	0.683	0.216	0.255	0.699	0.12		
UB	0.527	0.721	0.75	0.913	0.593	0.807	0.871	0.754	0.793	0.492	0.636	0.777	0.227	0.644	

The HTMT threshold used in this study is 0.85, and the maximum acceptable range is 0.90 (Hair et al., 2017), which meets the acceptance criteria of most academic journals. The analysis found that the HTMT values of most construct pairs were lower than 0.85, indicating that there was good differentiation between the constructs. For example, the HTMT of device empowerment (DE) and perceived risk (PR) was 0.263, which was significantly lower than the standard threshold. The HTMT value of intention and usage behavior (UB) was 0.913, slightly higher than 0.85, indicating that there was a certain degree of behavioral coupling between the two constructs. However, this high value is consistent with its theoretical causal logic. Behavioral intention itself is a leading variable of usage behavior (Ajzen, 1991). It does not mean that the scale design is invalid, but a reasonable mapping between theory and empirical evidence.

4.6.2.4 Discriminant validity analysis of Fornell-Larcker

Table 4.22
Fornell-Larcker (Gen Y)

	DE	E	EC	UI	MR	PB	PFC	PHB	PR	PSEF	PU	Pse	Psu	SI	UB
DE	0.659														
E	0.601	0.76													
EC	0.654	0.601	0.712												
UI	0.658	0.597	0.738	0.685											
MR	0.401	0.29	0.588	0.45	0.925										
PB	0.375	0.709	0.592	0.745	0.603	0.814									
PFC	0.264	0.443	0.381	0.668	0.703	0.521	0.972								
PHB	0.274	0.362	0.355	0.639	0.503	0.84	0.838	0.922							
PR	0.263	0.411	0.401	0.621	0.657	0.406	0.804	0.856	0.941						
PSEF	0.643	0.549	0.294	0.589	0.318	0.48	0.309	0.321	0.304	0.645					
PU	0.681	0.557	0.708	0.522	0.349	0.345	0.249	0.305	0.264	0.707	0.711				
Pse	0.43	0.363	0.486	0.572	0.753	0.68	0.878	0.63	0.83	0.41	0.275	0.889			
Psu	0.259	0.416	0.522	0.227	0.118	0.252	0.156	0.111	0.148	0.333	0.229	0.15	0.954		
SI	0.289	0.287	0.611	0.49	0.88	0.662	0.729	0.588	0.683	0.216	0.255	0.699	0.12	0.914	
UB	0.527	0.721	0.75	0.513	0.593	0.797	0.771	0.754	0.793	0.492	0.636	0.777	0.227	0.644	0.756

In the results of this study, the main diagonal values of all variables are their respective √AVEs, which are all higher than the correlation coefficients of other variables in their columns. The √AVE of Device Empowerment (DE) is 0.659, which is significantly greater than its correlation with variables such as Usage Behavior (UB) (0.527) and Intention to Use (0.658), meeting the requirements of discriminant validity. The √AVE of Perceived Financial Cost (PFC) is 0.972, which is also much higher than its correlation coefficient with Perceived Barrier (PB) (0.759) or Perceived Risk (PR) (0.947). Even though these constructs are similar in theory, the scale still shows good construct separation. The Fornell–Larcker criterion is fully met in this study, verifying that there is sufficient measurement independence between the constructs.

4.7 VIF

Table 4.23
VIF

Item	Baby Boomers VIF	Gen Y VIF
DE1	4.857	1.049
DE2	4.171	1.042
DE3	4.765	1.052
DE4	4.583	1.022
DE5	3.916	1.031
DE6	4.859	1.055
E1	4.612	1.009
E2	3.914	1.005
E3	4.461	1.004
EC2	3.944	1.008
EC3	4.191	1.003
EC4	4.421	1.003
EC1	1.69	1.003
UI11	4.547	1.155
UI12	2.101	1.143
UI21	4.927	1.049
UI22	4.959	1.05
UI31	2.775	1.008
UI32	2.688	1.057
MR2	3.7	1.9
MR3	7.677	1.727
MR1	3.186	1.883
PB1	2.8	1.185
PB2	2.923	1.219
PB3	2.179	1.297
PB4	2.292	1.281
PB5	3.381	1.325
PFC1	3.95	3.107
PFC2	3.359	3.661
PFC3	3.122	3.518
PFC4	4.625	3.409
PHB1	4.444	2.586
PHB2	4.8	2.527
PHB3	4.824	2.597
PHB4	3.055	2.446
PHB5	4.79	2.467
PR1	4.934	3.771
PR2	2.51	3.292
PR3	3.628	3.599
PR4	2.231	3.13
PR5	3.182	3.183
PR6	2.112	3.132
PSU1	3.811	6.687
PSU2	3.193	4.181

PSU3	2.675	3.169
PSU4	3.685	3.242
PSE1	2.611	2.007
PSE2	2.795	1.862
PSE3	2.677	1.953
PSE4	3.003	1.847
PSE5	3.077	1.791
PSEF1	3.326	1.033
PSEF2	2.839	1.040
PSEF3	4.957	1.037
PSEF4	8.451	1.039
PSEF5	3.998	1.054
PSEF6	3.751	1.024
SI1	2.821	2.171
SI2	2.521	2.081
SI3	2.591	2.392
SI4	3.259	2.331
SI5	3.063	2.083
PU1	2.800	1.013
PU2	2.075	1.008
PU3	1.055	1.010
PU4	3.157	1.003
UB11	4.263	1.233
UB12	3.323	1.318
UB21	4.826	1.020
UB22	4.784	1.010
UB31	3.457	1.213
UB32	3.033	1.229

In the structural equation model, in order to ensure that there is no statistical confusion between measurement indicators due to similar or repeated content and to identify whether there is significant collinearity between measurement items, it is necessary to test the Variance Inflation Factor of each measurement item (Thompson et al., 2017). The mobile limitation 3 item (VIF 7.677) of Baby Boomers may have a high overlap with MR2 or other control variables in terms of expression, but it does not exceed 10. The perceived self-efficacy 4 item (VIF 8.451) of Baby Boomers may have a high overlap with MR2 or other control variables in terms of expression, but it does not exceed 10. The perceived sensitivity (VIF 6.687) of Gen Y may be due to its broad

wording or extremely similar expression to Psu2, Psu3, etc. Cohen et al., (2003) pointed out that VIF < 10 does not constitute an urgent problem and can be retained.

4.8 KMO and Bartlett's Test

According to Creswell and Creswell (2018), there are two methods to assess validity: construct validity and content validity. The Kaiser-Meyer-Olkin (KMO) measure is an effective method for checking the structural validity. The results of this study indicate that all KMO values (Gen Y and Baby Boomer) are more significant than 0.7, indicating that the data structure is valid. In Appendices C and D, the researchers provided the results of the reliability and validity tests of smartPls to supplement the shortcomings of SPSS in this regard.

Table 4.24
KMO and Bartlett's Test

		Gen Y	Baby boomer
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.885	.949
Bartlett's Test of Sphericity	Approx. Chi-Square	4232.485	4232.485
	df	120	120
	Sig.	.000	.000

4.9 Hypothesis Testing

4.9.1 Path Analysis Between Variables of Baby Boomers

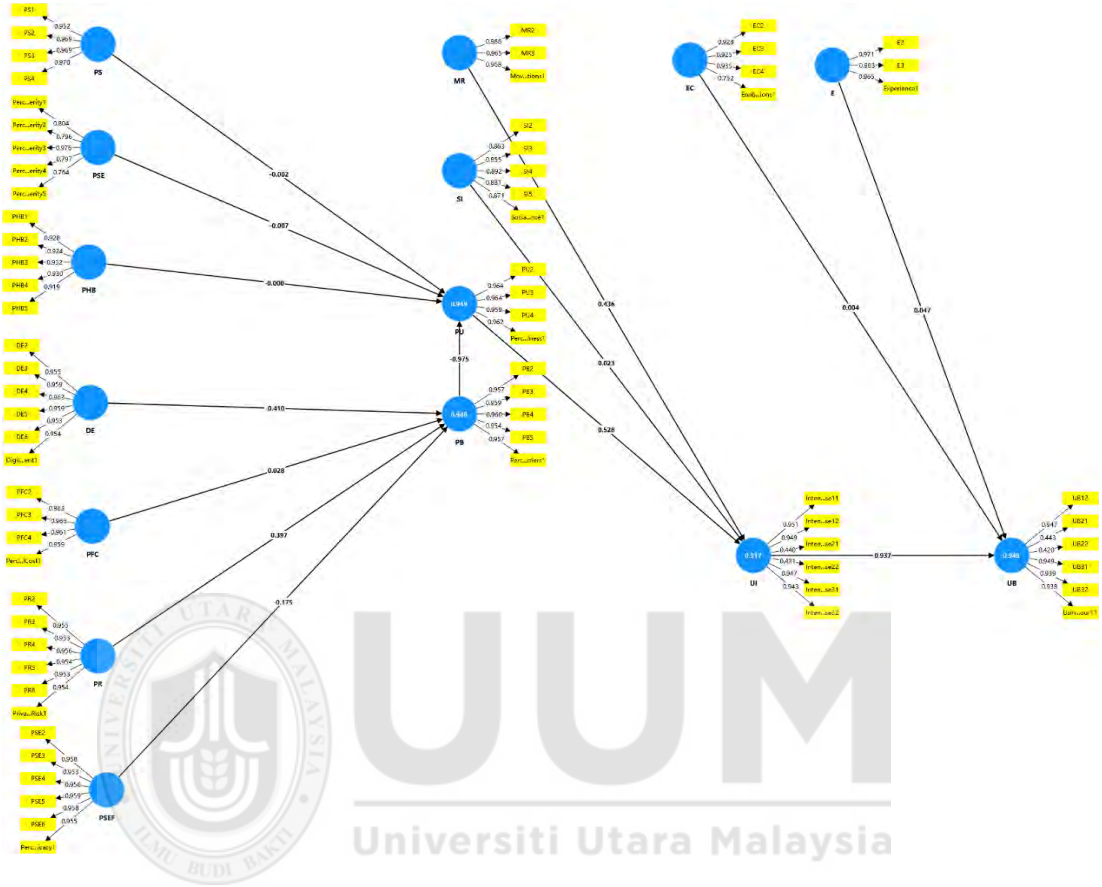


Figure 4.5 Correlation Analysis of Baby Boomers

Table 4.25
Path Analysis Between Variables of Baby Boomers

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values	Hypothetical results
DE -> PB	-0.410	-0.401	0.078	5.253	0.000	The more powerful the digital device, the lower the perceived barrier
E -> UB	0.047	0.047	0.024	1.968	0.049	The more technical experience, the more frequent the behavior

EC -> UB	0.004	0.005	0.025	0.162	0.871	Not statistically significant
MR -> UI	0.436	0.442	0.084	5.186	0.000	The clearer the action restrictions, the higher the intention to use
PB -> PU	-0.975	-0.975	0.005	191.473	0.000	The higher the perceived barrier, the lower the perceived usefulness
PB -> UI	-0.419	-0.425	0.074	5.662	0.000	The higher the perceived barrier, the lower the using intention
PFC -> PB	0.028	0.028	0.015	1.934	0.053	Not statistically significant
PHB -> PU	0.000	0.001	0.014	0.028	0.978	Not statistically significant
PR -> PB	0.397	0.392	0.071	5.604	0.000	The greater the privacy risk, the greater the perceived barrier
PS -> PU	-0.002	-0.003	0.016	0.102	0.919	Not statistically significant
PSE -> PU	-0.007	0.002	0.020	0.323	0.747	Not statistically significant
PSEF -> PB	-0.175	-0.189	0.072	2.413	0.016	The greater the self-efficacy, the lower the perceived barriers
PU -> UI	0.528	0.522	0.086	6.157	0.000	The stronger the perceived usefulness, the higher the intention to use
SI -> UI	0.023	0.023	0.022	1.028	0.304	Not statistically significant
UI -> UB	0.937	0.937	0.021	44.078	0.000	The stronger the intention to use, the higher the frequency of use

The results show that there are eight path relationships that reach statistical significance ($P < 0.05$). In the path explaining Perceived Barriers (PB), Digital Device Accessibility (DE → PB, $\beta = -0.410$, $T = 5.253$, $P < 0.001$) is significantly negatively correlated, indicating that if the elderly have more available digital devices, their subjective sense of barriers will be significantly reduced; at the same time, Privacy Risk (PR → PB, $\beta = 0.397$, $T = 5.604$, $P < 0.001$) significantly increases their barrier

perception, indicating that the elderly are more likely to have psychological rejection when facing the risk of data leakage. In addition, Self-efficacy (PSEF → PB, β = -0.175, T = 2.413, P = 0.016) also shows a negative impact, which means that elderly users with higher self-control ability are less likely to perceive barriers to digital use. These results are consistent with the view that perceived barriers in the health belief model are important constraints on behavior.

In the prediction path of perceived usefulness (PU), perceived barriers (PB → PU, β = -0.975, T = 191.47, P < 0.001) is the only significant path with a huge path coefficient, indicating that subjective barriers almost completely suppress their positive cognition of the utility of the new retail system, showing the high sensitivity of the elderly group to system complexity and risk. In the formation path of usage intention (UI), perceived usefulness (PU → UI, β = 0.528, T = 6.157, P < 0.001) and action restrictions (MR → UI, β = 0.436, T = 5.186, P < 0.001) have significant positive effects. Among them, the influence of PU verifies the core mechanism of the TAM model, that is, utility cognition can enhance intention formation; while the path of MR reflects that the real pressure under the background of the epidemic has promoted the passive adoption of digital means. In addition, although the social influence (SI → UI) is positive, it does not reach a significant level (P = 0.304). Perhaps the elderly are less dependent on the opinions of their peers than the young group.

Finally, in the formation of usage behavior (UB), usage intention (UI → UB, β = 0.937, T = 44.078, P < 0.001) shows an overwhelming direct influence, and the path coefficient is close to 1, reflecting a strong predictive effectiveness, which is also in line with the basic logic of intention-driven behavior in the UTAUT and TPB models.

Usage experience (E → UB, β = 0.047, T = 1.968, P = 0.049) is also marginally significant, indicating that the past experience of the elderly group has a certain supporting effect on the persistence of behavior.

PFC → PB (P = 0.053) marginally significant, indicating that although economic investment has an impact, the impact on the elderly is not as strong as device availability and privacy risks. PHB → PU, PSE → PU, PS → PU none of them are significant, suggesting that the factors such as health benefits and perceived susceptibility in the health belief model have a relatively weak influence on the digital behavior of the elderly. SI → UI also failed the significance test, which may be because elderly users are less influenced by peer networks, and their technology use is more driven by personal motivation and real-life pressure. EC → UB is completely insignificant, suggesting that technological convenience is not decisive for the final behavior, and may be more of a pre-moderating factor rather than a direct motivation.

4.9.2 Path Analysis Between Variables of Gen Y

Table 4.26
Path Analysis Between Variables of Gen Y

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values	Hypothetical results
DE -> PB	-0.084	-0.089	0.073	1.145	0.252	Not statistically significant
E -> UB	0.145	0.061	0.153	0.945	0.345	Not statistically significant
EC -> UB	0.189	0.186	0.088	2.148	0.032	The greater facilitating conditions, the higher the frequency of use
UI -> UB	0.545	0.547	0.046	11.845	0.000	The greater using intention,

						the higher the frequency of use
MR -> UI	0.010	0.016	0.093	0.105	0.916	Not statistically significant
PB -> UI	-0.419	-0.425	0.074	5.662	0.000	The higher Perceived barriers, the lower using intention
PB -> PU	-0.160	-0.107	0.157	1.014	0.311	Not statistically significant
PFC -> PB	0.529	0.511	0.131	4.036	0.000	The higher perceived financial cost, the higher the Perceived barriers
PHB -> PU	0.224	0.193	0.126	1.773	0.076	Not statistically significant
PR -> PB	0.206	0.211	0.129	1.598	0.110	Not statistically significant
PSEF -> PB	0.084	0.105	0.047	1.786	0.074	Not statistically significant
PU -> UI	-0.036	-0.052	0.080	0.455	0.649	Not statistically significant
Pse -> PU	0.043	0.018	0.192	0.225	0.822	Not statistically significant
Psu -> PU	0.119	0.096	0.118	1.002	0.317	Not statistically significant
SI -> UI	-0.177	-0.171	0.095	1.865	0.062	Not statistically significant

The study shows that the path of perceived barriers (PB) on usage intention (UI) is significant ($\beta = -0.419$, $T = 5.662$, $P < 0.001$), and usage intention is also highly significantly related to actual usage behavior (UB) ($\beta = 0.545$, $T = 11.845$, $P < 0.001$). Perceived financial cost (PFC) has a significant positive predictive effect on perceived barriers ($\beta = 0.529$, $T = 4.036$, $P < 0.001$), which means that the Gen Y are more sensitive to cost concerns, which is an important source of their sense of barriers. The EC → UB path is significant ($\beta = 0.189$, $P = 0.032$), indicating that the technical environment (such as network facilities) has a driving effect on actual usage.

The PB (Perceived Barriers) → PU (Perceived Usefulness) path did not reach a significant level (β = −0.160, P = 0.311), and the PU (Perceived Usefulness) → UI (Using Intention) path was also not significant (β = −0.036, P = 0.649), indicating that perceived usefulness failed to constitute an effective cognitive pathway in this population, and its mediating position did not hold. The PHB → PU path was marginally significant (β = 0.224, P = 0.076), indicating that health beliefs still have a weak effect on cognitive usefulness, but it is unstable. SI → UI was also marginally significant (β = −0.177, P = 0.062). Interestingly, its path was negative, which may indicate that Generation Y may have resistance to social influence. Several other paths did not reach a significant level, indicating that their influence mechanism is not strong in Generation Y.

4.9.3 R ²Comparison

Table 4.27
R ²Comparison results

Latent Variable	R-square (Baby Boomers)	R-square adjusted (Baby Boomers)	R-square (Gen Y)	R-square adjusted (Gen Y)
PB	0.968	0.967	0.593	0.588
PU	0.949	0.948	0.047	0.036
UB	0.948	0.947	0.364	0.358
UI	0.917	0.915	0.294	0.286

R ² measures the explanatory power of an exogenous variable on an endogenous variable, that is, how much of the variance of the endogenous variable can be explained by the model (Hair et al., 2019). The adjusted R ²further controls the inflation effect of the number of independent variables on R ², providing a more conservative and stable estimate of explanatory power. In the Baby Boomers group, the R ²of all endogenous variables showed extremely high explanatory power (All > 0.9). The explanatory

power of the structural model of the Generation Y group was significantly weaker, and the effects of PFC and PR on PB (R^2= 0.593) were relatively stable. The perceived usefulness of the system (R^2= 0.047) of Generation Y was not fully captured by the model and was judged to be unrelated to health factors. The intention to use (R^2= 0.294) of Generation Y was partially explained by the structural model, but there was still a large unexplained space. The model can explain a certain proportion of the variability in UB (R^2= 0.364).

4.9.4 Model fit comparison

Table 4.28
Model fit comparison results

Fit Index	Baby Boomers - Saturated	Baby Boomers - Estimated	Gen Y - Saturated	Gen Y - Estimated
SRMR	0.058	0.059	0.061	0.082
d_ULS	8.863	9.169	9.816	17.587
d_G	5.177	5.426	3.412	3.673
Chi-square	4551.816	4672.323	5790.162	6059.8
NFI	0.824	0.82	0.64	0.623

When using partial least squares structural equation modeling (PLS-SEM), model goodness of fit is used as an auxiliary evaluation criterion to provide a description of the overall rationality of the model. SRMR is currently one of the most commonly used fit indicators for PLS-SEM. The lower the value, the smaller the residual between the model and the actual data. 0.08 is usually used as the acceptable threshold (Hair et al., 2019). In the Baby Boomers group, SRMR = 0.059 (Estimated model), which is significantly lower than 0.08, showing a good fit performance. In the Gen Y group, SRMR = 0.082, which is slightly higher than the threshold and can be ignored.

d_ULS and d_G are used to evaluate the global fit of the latent variable model. The d_ULS = 9.169 and d_G = 5.426 of the Baby Boomers group are significantly better than the d_ULS = 17.587 and d_G = 3.673 of Generation Y, indicating that the latent variable estimates of the elderly group match the covariance matrix better. Chi-Square Variance was used to evaluate model fit. The chi-square value of Baby Boomers is 4672.32, which is significantly better than 6059.80 of Generation Y, further supporting the superiority of the former's path model fit.

NFI is the comparison between the model fitting of this study and the null model, and a value greater than 0.9 is ideal. The NFI of the Baby Boomers model is 0.820, which is close to the recommended standard (0.90), while the NFI of Generation Y is only 0.623, indicating that its structural model does not fit well at the overall level.

4.9.5 Q ²Prediction Correlation Comparison

Table 4.29
Q ²Prediction Correlation Comparison results

Latent Variable	Q ²(=1-SSE/SSO)(Baby Boomers)	Q ²(=1-SSE/SSO)(Gen Y)
DE	0	0
E	0	0
EC	0	0
MR	0	0
PB	0.882	0.24
PFC	0	0
PHB	0	0
PR	0	0
PS	0	0
PSE	0	0
PSEF	0	0
PU	0.871	-0.006
SI	0	0
UB	0.616	0.099
UI	0.597	0.053

According to the recommendations of Chin (1998) and Hair et al. (2019), $Q^2 > 0$ indicates that the model has predictive relevance to the corresponding endogenous variable, where $Q^2 \geqslant 0.02$, 0.15, and 0.35 represent small, medium, and large predictive validity, respectively. In the Baby Boomers group, the model showed a high predictive relevance for perceived barriers (PB, $Q^2 = 0.882$), perceived usefulness (PU, $Q^2 = 0.871$), usage behavior (UB, $Q^2 = 0.616$), and usage intention (UI, $Q^2 = 0.597$), all of which far exceeded the threshold of 0.35 and were classified as high-level predictions. This result shows that the model in this study has a strong explanatory and predictive power in explaining the use behavior of mobile health technology among the elderly.

The analysis of Q^2 values revealed significant differences in the predictive validity of the structural model among different generational groups. The overall Q^2 performance of the Generation Y group was relatively weak, and only showed a certain predictive correlation for perceived barriers (PB, $Q^2 = 0.240$) and usage behavior (UB, $Q^2 = 0.099$). Although the intention to use variable ($Q^2 = 0.053$) exceeded the critical value of 0.02, it only had weak predictive validity. In addition, perceived usefulness (PU, $Q^2 = -0.006$) showed a negative value, indicating that the model lacked predictive ability for this variable in the Gen Y group, which may also reveal that this group does not regard usefulness as a key motivation in the use of digital technology.

4.9.6 Outer Model Evaluation

Table 4.30
Outer Model results

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values	Significance
DE2 <- DE	0.955	0.955	0.004	232.311	0.000	Significant

DE3 <- DE	0.959	0.959	0.004	250.114	0.000	Significant
DE4 <- DE	0.963	0.963	0.003	279.679	0.000	Significant
DE5 <- DE	0.959	0.959	0.004	241.207	0.000	Significant
DE6 <- DE	0.953	0.953	0.004	243.839	0.000	Significant
DE1<- DE	0.954	0.954	0.004	238.989	0.000	Significant
E1<- E	0.965	0.965	0.003	287.400	0.000	Significant
E2 <- E	0.971	0.971	0.003	315.177	0.000	Significant
E3 <- E	0.963	0.963	0.004	253.659	0.000	Significant
EC2 <- EC	0.928	0.928	0.011	83.495	0.000	Significant
EC3 <- EC	0.925	0.924	0.014	64.289	0.000	Significant
EC4 <- EC	0.935	0.933	0.012	81.205	0.000	Significant
EC1<- EC	0.752	0.747	0.060	12.605	0.000	Significant
UI11 <- UI	0.951	0.951	0.005	192.824	0.000	Significant
UI12 <- UI	0.949	0.949	0.006	163.329	0.000	Significant
UI21 <- UI	0.440	0.435	0.063	7.005	0.000	Significant
UI22 <- UI	0.431	0.427	0.064	6.732	0.000	Significant
UI31 <- UI	0.947	0.947	0.006	166.827	0.000	Significant
UI32 <- UI	0.943	0.944	0.006	167.010	0.000	Significant
MR2 <- MR	0.966	0.966	0.003	293.639	0.000	Significant
MR3 <- MR	0.965	0.965	0.004	246.532	0.000	Significant
MR1 <- MR	0.968	0.968	0.003	307.129	0.000	Significant
PB1 <- PB	0.957	0.957	0.004	231.636	0.000	Significant
PB2 <- PB	0.957	0.957	0.004	247.197	0.000	Significant
PB3 <- PB	0.959	0.959	0.004	244.157	0.000	Significant
PB4 <- PB	0.960	0.960	0.004	264.566	0.000	Significant
PB5 <- PB	0.954	0.954	0.004	234.048	0.000	Significant
PFC2 <- PFC	0.963	0.963	0.003	299.146	0.000	Significant
PFC3 <- PFC	0.966	0.966	0.003	313.499	0.000	Significant
PFC4 <- PFC	0.961	0.961	0.003	303.113	0.000	Significant
PHB1 <- PHB	0.928	0.905	0.097	9.521	0.000	Significant
PHB2 <- PHB	0.924	0.899	0.102	9.055	0.000	Significant
PHB3 <- PHB	0.932	0.908	0.097	9.636	0.000	Significant
PHB4 <- PHB	0.930	0.905	0.101	9.180	0.000	Significant
PHB5 <- PHB	0.919	0.894	0.104	8.838	0.000	Significant
PR2 <- PR	0.955	0.955	0.004	241.459	0.000	Significant
PR3 <- PR	0.953	0.954	0.003	272.959	0.000	Significant
PR4 <- PR	0.956	0.956	0.004	240.254	0.000	Significant
PR5 <- PR	0.954	0.954	0.004	253.368	0.000	Significant
PR6 <- PR	0.953	0.954	0.004	266.612	0.000	Significant

PS1 <- PS	0.952	0.933	0.097	9.770	0.000	Significant
PS2 <- PS	0.969	0.944	0.101	9.627	0.000	Significant
PS3 <- PS	0.969	0.944	0.098	9.871	0.000	Significant
PS4 <- PS	0.970	0.948	0.096	10.069	0.000	Significant
PSE2 <- PSEF	0.958	0.958	0.004	254.943	0.000	Significant
PSE3 <- PSEF	0.953	0.953	0.004	246.489	0.000	Significant
PSE4 <- PSEF	0.956	0.957	0.004	244.427	0.000	Significant
PSE5 <- PSEF	0.959	0.959	0.004	244.921	0.000	Significant
PSE6 <- PSEF	0.958	0.958	0.004	258.518	0.000	Significant
PU2 <- PU	0.964	0.964	0.004	260.523	0.000	Significant
PU3 <- PU	0.964	0.964	0.004	273.285	0.000	Significant
PU4 <- PU	0.959	0.959	0.004	260.781	0.000	Significant
PFC1 <- PFC	0.959	0.959	0.003	276.301	0.000	Significant
PS1 <- PSE	0.804	0.731	0.212	3.799	0.000	Significant
PS2 <- PSE	0.796	0.736	0.213	3.742	0.000	Significant
PS3 <- PSE	0.976	0.777	0.272	3.588	0.000	Significant
PS4 <- PSE	0.797	0.742	0.214	3.720	0.000	Significant
PS5 <- PSE	0.764	0.735	0.233	3.276	0.001	Significant
PU1 <- PU	0.962	0.962	0.004	262.378	0.000	Significant
PSEF1 <- PSEF	0.955	0.955	0.004	244.495	0.000	Significant
PR1 <- PR	0.954	0.954	0.004	259.497	0.000	Significant
SI2 <- SI	0.863	0.858	0.031	28.183	0.000	Significant
SI3 <- SI	0.855	0.850	0.034	25.231	0.000	Significant
SI4 <- SI	0.892	0.888	0.024	37.465	0.000	Significant
SI5 <- SI	0.881	0.875	0.030	29.435	0.000	Significant
SI1 <- SI	0.871	0.868	0.027	31.925	0.000	Significant
UB12 <- UB	0.947	0.947	0.005	174.745	0.000	Significant
UB21 <- UB	0.443	0.439	0.065	6.805	0.000	Significant
UB22 <- UB	0.420	0.415	0.067	6.310	0.000	Significant
UB31 <- UB	0.949	0.949	0.006	159.744	0.000	Significant
UB32 <- UB	0.939	0.939	0.007	139.277	0.000	Significant
UB11 <- UB	0.938	0.938	0.007	136.092	0.000	Significant

According to the standards of Hair et al. (2022), the load value should be ≥ 0.708 to indicate that the indicator has a high explanatory power and can explain at least 50% of the variance of the latent variable to which it belongs. Although the study has given

the evolution results of external loads such as AVE and Cronbach's alpha. The researchers still provided some content of the external loads. The vast majority of indicator load values are higher than 0.95, the T values are all over 200, and the significance is better than the 0.001 level ($p < 0.001$), showing extremely strong indicator reliability. The study shows that the measurement model of this group shows a high degree of consistency at the indicator level, and all items are statistically significant.

4.9.7 Hypothesis Testing Result

Table 4.31
Summary of Hypothesis Testing

Hypothesis		**Result**	
		Gen Y	Baby Boomer
H_1	In the use of new retail e-commerce assistants, instant retail and self-checkout systems, perceived susceptibility to the pandemic affects people's judgments of the perceived usefulness of their technologies.	Irrelevant	Irrelevant
H_2	In the use of new retail e-commerce assistants, online shopping and self-checkout systems, perceived severity to the pandemic affects people's judgments of the perceived usefulness of their technologies.	Irrelevant	Irrelevant
H_3	In the use of new retail e-commerce assistants, instant retail and self-checkout systems, perceived health benefits to the technologies affect people's judgments of the perceived usefulness of their technologies.	Irrelevant	Irrelevant

H_4	In the use of new retail e-commerce assistants, instant retail and self-checkout systems, digital equipment requires an impact on people's perceived barriers to the use of new retail technologies.	Irrelevant	Support
H_5	In the use of new retail e-commerce assistants, instant retail and self-checkout systems, perceived financial cost has an impact on people's perceived barriers to the use of new retail technologies.	Support	Irrelevant
H_6	In the use of new retail e-commerce assistants, instant retail and self-checkout systems, privacy risk an impact on people's perceived barriers to the use of new retail technologies.	Irrelevant	Support
H_7	In the use of new retail e-commerce assistants, instant retail, and self-checkout systems, self-efficacy has an impact on people's perceived barriers to the use of new retail technologies.	Irrelevant	Support
H_8	In the use of new retail e-commerce assistants, instant retail and self-checkout systems, barriers perceived an impact on people's perceived usefulness to the use of new retail technologies.	Irrelevant	Support
H_9	In the use of new retail e-commerce assistants, instant retail and self-checkout systems, barriers perceived an impact on people's intention to use new retail technologies.	Support	Support
H_{10}	In the use of new retail e-commerce assistants, instant retail and self-checkout systems, movement restrictions an impact on people's intention to use of new retail technologies.	Irrelevant	Support
H_{11}	In the use of new retail e-commerce assistants, instant retail and self-checkout systems, social	Irrelevant	Irrelevant

	influence an impact on people's intention to use of new retail technologies.		
H_{12}	In the use of new retail e-commerce assistants, instant retail and self-checkout systems, perceived usefulness an impact on people's intention to use of new retail technologies.	Irrelevant	Support
H_{13}	In the use of new retail e-commerce assistants, instant retail and self-checkout systems, facilitating conditions an impact on people's using behaviour of new retail technologies.	Support	Irrelevant
H_{14}	In the use of new retail e-commerce assistants, instant retail and self-checkout systems, intention to use an impact on people's using behaviour of new retail technologies.	Support	Support
H_{15}	In the use of new retail e-commerce assistants, instant retail and self-checkout systems, experience an impact on people's using behaviour of new retail technologies.	Irrelevant	Support
H_{16}	In the use of new retail e-commerce assistants, instant retail and self-checkout systems, Perceived usefulness as mediating variables between perceived barriers and using intention of new retail technologies.	Irrelevant	Support

CHAPTER FIVE

FINDING AND CONCLUSION

5.1 Introduction

This chapter describes the research findings. Based on the data results presented in Chapter 4, this study aimed to describe the differences between the Chinese Gen Y and Baby Boomer populations. It also includes a review of the overall research process, highlighting the limitations and shortcomings of the study and proposing future improvement plans.

5.2 Finding

5.2.1 Descriptive findings

5.2.1.1 Health Factors of HBM model

Table 5.1
Health Factors of HBM model

	Groups	N	Mean	Std. Deviation	Attitude
PSU (Perceived Susceptibility)	*Gen Y*	200	2.8763	1.18194	Uncertain
PSE (Perceived Severity)	*Gen Y*	200	3.4590	.97914	Agree
PHB (Perceived Health Benefits)	*Gen Y*	200	3.1360	1.05139	Uncertain
PSU (Perceived Susceptibility)	*Baby B*	199	3.1106	1.32587	Uncertain
PSE (Perceived Severity)	*Baby B*	199	4.1839	.69757	Agree
PHB (Perceived Health Benefits)	*Baby B*	199	2.0271	.97870	Disagree

This study used the three key dimensions of the Health Belief Model (HBM) - perceived susceptibility (PSU), perceived severity (PSE) and perceived health benefits (PHB) - to conduct a structural comparison of the health attitudes of Generation Y and Baby Boomers in China. The statistical results are shown in the table. The two generations showed significant differences in their perception of epidemic risks and confidence in technological intervention.

At the level of perceived susceptibility (PSU), both Generation Y (M = 2.88, SD = 1.18) and Baby Boomers (M = 3.11, SD = 1.33) showed a neutral (Uncertain) attitude. This shows that the two generations have reservations about the possibility of being attacked by similar infectious diseases in the future, neither absolutely denying nor showing strong concerns. As Li et al. (2024) pointed out, Chinese society has gradually adapted to the normalization of treatment for mild cases of Omicron, so the perception of infection risk among young people has shown a downward trend.

However, in terms of perceived severity (PSE), the attitudes of the two generations differ significantly. The score of Baby Boomers was as high as 4.18 (SD = 0.70), which is at the agree level, while Generation Y also reached the agree range (M = 3.46, SD = 0.98), but the degree was relatively mild. This result reflects that the elderly group is still highly alert to the threat of infectious diseases, which may be closely related to their increased health vulnerability and personal experience in the epidemic. Relatively speaking, although Generation Y accepts the severity of the disease, the risk perception is not extreme, reflecting a higher adaptability and ability to screen medical information (Taylor, 2020).

In terms of perceived health benefits (PHB), the generational differences are particularly significant. Generation Y gave a neutral assessment of the health benefits of technology-assisted scenarios such as instant retail, e-commerce assistants, and self-checkout (M = 3.14, SD = 1.05), while Baby Boomers showed a clear disagreement (M = 2.03, SD = 0.98). This means that Generation Y is more inclined to believe that technology can improve life safety to a certain extent, although they are not completely convinced; while Baby Boomers have very low trust in such technologies. This difference may be due to the technological familiarity and media contact preferences of different generations, or it may be related to the closed space transmission mechanism revealed by early studies (Yan & Lan, 2020). In addition, Burdzik (2021) pointed out that supermarket plastic bags and delivery personnel may still constitute transmission media in the instant retail process, and this view may have a greater influence among the elderly.

5.2.1.2 Barrier Factors of TORAOA model

Table 5.2
Barrier Factors of TORAOA model

	Group	N	Mean	Std. D	Attitude
DE (Digital Equipment)	*Gen Y*	200	4.5125	.20798	Strongly agree
PFC (Perceived Financial Cost)	*Gen Y*	200	3.2125	1.25758	Uncertain
PR (Privacy Risk)	*Gen Y*	200	3.3800	1.07665	Uncertain
PS (Perceived self-efficacy)	*Gen Y*	200	4.4792	.18825	Strongly agree
PB (Perceived barriers)	*Gen Y*	200	1.9890	.47835	Disagree
DE (Digital Equipment)	*Baby B*	199	3.4615	1.37209	Agree
PFC (Perceived Financial Cost)	*Baby B*	199	3.0075	1.40524	Uncertain
PR (Privacy Risk)	*Baby B*	199	2.5477	1.34448	Disagree
PS (Perceived self-efficacy)	*Baby B*	199	3.4188	1.38604	Agree
PB (Perceived barriers)	*Baby B*	199	2.5558	1.37086	Disagree

The resistance factors of Generation Y and Baby Boomers in the use of digital technology cover five key dimensions: Digital Equipment (DE), Perceived Financial Cost (PFC), Perceived Privacy Risk (PR), Perceived Self-efficacy (PS), and Perceived Barriers (PB). Statistics show that the two generations show structural differences in technology adaptability, cost sensitivity, risk awareness, and belief mechanisms, which reflect their respective social backgrounds and the degree of internalization of technological culture.

Digital Equipment Mastery (DE), Generation Y shows a significant lead (M = 4.51, SD = 0.21, attitude: strongly agree), while Baby Boomers' scores are moderately high (M = 3.46, SD = 1.37, attitude: agree). This difference is not only a manifestation of the digital divide, but also reflects the reality that Generation Y is highly dependent on and proficient in digital tools in daily life and workplace scenarios. Related research indicates that Generation Y shows a tendency to continuously optimize time efficiency, communication effectiveness, and mobile technology adaptability (Alam et al., 2020; Raslie, 2021). They have internalized smartphones, tablets, and instant retail systems as an important part of their daily lives (Lissitsa & Kol, 2021).

Perceived finance costs (PFC), both generations showed a neutral attitude (Gen Y: M = 3.21; Baby Boomers: M = 3.01), but the standard deviation of Generation Y (SD = 1.26) was slightly lower, indicating that they had a more consistent assessment of costs. This result shows that although digital technology involves a certain amount of economic investment, Generation Y tends to regard it as an acceptable transaction cost as long as it can bring efficiency improvements or convenience enhancements; while the elderly group has a stronger sense of economic burden, especially in the context of fixed income, and cost perception is more likely to affect their adoption decisions.

Perceived privacy risk (PR), Generation Y's attitude is still neutral (M = 3.38, SD = 1.08), while Baby Boomers show a clear disagreement attitude (M = 2.55, SD = 1.34). Interestingly, this result subverts the assumption in traditional literature that older people are more concerned about privacy security (Lustgarten et al., 2020). Possible reasons include: (1) The elderly have a high level of trust in the legal system and believe that China's Internet governance mechanism can protect their privacy and security; (2) Some elderly people believe that they do not have enough privacy that is vulnerable to being violated, thus reducing their risk awareness; (3) Generation Y is more familiar with big data ecology and information leakage cases. Although they still choose to use technology, they retain a critical awareness of platform manipulation of data.

Perceived self-efficacy (PS), Generation Y again showed a significant advantage (M = 4.48, SD = 0.19, attitude: strongly agree), while Baby Boomers scored in the agree range (M = 3.42, SD = 1.39). It is worth noting that although the overall self-assessed efficacy of Baby Boomers is not as good as that of Generation Y, it contrasts with the view in previous studies that the elderly have low technical self-efficacy (Jokisch et al., 2020). This study focuses on the elderly population in first-tier cities such as Shanghai, China. The high technology penetration rate and socialized learning mechanism in this region may effectively enhance the elderly's confidence in the operation of technologies such as supermarket self-service checkout and instant retail.

Perceived barriers (PB), both generations showed an attitude of disagreement, which means that they do not think there are substantial obstacles in the use of technology. However, the scores of Generation Y were lower (M = 1.99, SD = 0.48) compared to Baby Boomers (M = 2.56, SD = 1.37), showing higher fluency in use and ability to

adapt to obstacles. In other words, Generation Y is more inclined to ignore possible problems in the use process and quickly solve them with digital literacy.

5.2.1.3 Factors of UTAUT

Table 5.3
Factors of UTAUT

	Group	N	Mean	Std. Deviation	Attitude
PU (Perceived usefulness)	*Gen Y*	200	4.4638	.25112	Strongly agree
PU	*Baby B*	199	3.4296	1.41134	Agree
SI (Social Influence)	*Gen Y*	200	3.4680	.90480	Agree
SI	*Baby B*	199	4.2452	.75329	Strongly agree
MR (Movement restrictions)	*Gen Y*	200	2.3767	1.03663	Disagree
MR	*Baby B*	199	3.4673	1.37923	Agree
EC (Facilitating conditions)	*Gen Y*	200	3.9938	.40291	Agree
EC	*Baby B*	199	4.0515	.94457	Agree
ITU A (Intention to use Instant retail)	*Gen Y*	200	3.9750	.61951	Agree
ITU A	*Baby B*	199	3.4497	1.42045	Agree
ITU B (Intention to use of e-commerce assistant)	*Gen Y*	200	2.0250	.58402	Disagree
ITU B	*Baby B*	199	2.0905	1.14784	Disagree
ITU C (Intention to use of Self-checkout system)	*Gen Y*	200	4.4375	.33974	Strongly agree
ITU C	*Baby B*	199	3.4372	1.34458	Agree
E (Experience)	*Gen Y*	200	4.4567	.30133	Strongly agree
E	*Baby B*	199	3.4255	1.40062	Agree
UB A (Using the behaviour of Instant retail)	*Gen Y*	200	3.9975	.60046	Agree
UB A	*Baby B*	199	3.4171	1.39874	Agree
UB B (Using the behaviour of an e-commerce assistant)	*Gen Y*	200	2.0100	.53977	Disagree
UB B	*Baby B*	199	2.1080	1.17514	Disagree

UB C (Using the behavior of a Self-checkout system)	*Gen Y*	200	3.9700	.58807	Agree
UB C	*Baby B*	199	3.4196	1.40654	Agree

Generation Y showed extremely high perceived usefulness (M = 4.46, SD = 0.25) and rich usage experience (M = 4.46, SD = 0.30), which is much higher than the scores of Baby Boomers (PU: M = 3.43; E: M = 3.43), which are only at the agree level. This gap reflects that Generation Y highly recognizes the efficiency improvement, service optimization and convenience of life that technology can bring, and has established a solid behavior pattern through repeated operations (Basheer et al., 2022; Kashef et al., 2021). In contrast, although the frequency of technology use has increased significantly among the elderly, there is still a structural gap in the degree of technology internalization, which is manifested in that the perception of the value of technology has not yet been fully transformed into deep cognitive recognition.

The average score given by Baby Boomers (M = 4.25, SD = 0.75) is higher than that of Generation Y (M = 3.47, SD = 0.90) in social influence, indicating that the elderly are more susceptible to the influence of family, neighbours or social opinions in the process of digital technology adoption. This is in stark contrast to Generation Y, who are more individualistic and have more autonomous technology choices, and the latter are more concerned with intrinsic motivation and task fit. Generation Y clearly disagrees that technology use is passively adopted due to mobility difficulties (M = 2.38, SD = 1.04). They prefer to shop in person, choose products independently, and have a high degree of spatial mobility. Baby Boomers scored higher on MR (M = 3.47, SD = 1.38, attitude: agree), indicating that they are more likely to passively turn to

online shopping or instant retail due to physical factors, public health events or traffic conditions.

Both generations showed high recognition of self-service checkout systems (ITU C and UB C) (Gen Y ITU C: M = 4.44, Baby B: M = 3.44), reflecting the widespread recognition of their perceived efficiency and autonomy. In contrast, both generations showed low intention and low behavior towards e-commerce assistants (Gen Y ITU B: M = 2.03; Baby B ITU B: M = 2.09), indicating that AI interaction has not yet met consumers' high-level needs in terms of context, emotions, and problem solving (Riquel, 2022). In addition, Generation Y's intention and behavior towards instant retail are significantly higher than those of the elderly (ITU A: M = 3.98 vs. 3.45; UB A: M = 4.00 vs. 3.42). This reflects the matching degree between fast-paced life and flexible delivery services, making Generation Y more receptive to such technology models and incorporating them into their daily life system.

Generation Y believes that new retail-related technologies (such as self-checkout systems, e-commerce assistants, and instant retail) are beneficial. They have sufficient experience with their usage and keenly feel the constraints imposed by society. Among these technologies, they tend to prefer self-checkout systems. This study corroborates past findings indicating the overall effectiveness of supermarket technologies. For instance, previous research has shown that self-checkout systems reduce queuing times and optimise service experiences; e-commerce assistants enhance response efficiency; and instant retail achieves a balance between people's busy work and shopping schedules (Brusch & Rappel et al., 2020; Kashef et al., 2021; Suddaby, 2021; Lyu & Fan, 2022; Wei, 2021; Mondol et al., 2021; Basheer et al., 2022; Khaiyr & Rogermann, 2022).

Generation Y refuses to acknowledge limitations imposed by mobility and their willingness and behaviour regarding using e-commerce assistants. Despite significant familial and work pressures in Shanghai, China (An et al., 2020), they still believe they have sufficient time and energy to visit supermarkets and select goods. Additionally, the shortcomings of e-commerce assistants point to their rigid response nature, unable to truly address consumers' desires (Riquel, 2022). For instance, when individuals encounter spoiled fruits or purchase products that include expired items, artificial intelligence often cannot substitute for the intervention of supermarket staff to resolve such issues. Therefore, Generation Y is reluctant to rely on AI responses.

Elderly individuals in the Shanghai region of China do not perceive mastering technology as brutal; they feel capable of using supermarket technology flexibly and accurately. This contradicts past research, which commonly suggested that elderly individuals have low self-efficacy (Jokisch et al., 2020). This could be related to the frequency and fashion of technological exposure among elderly individuals in developed regions. Older adults with higher frequencies of technological exposure tend to be more adept at using various digital technologies (Jokisch et al., 2020).

Elderly individuals in the Shanghai region commonly possess at least one smartphone or tablet capable of instant retail. This suggests that the smartphone coverage rate among elderly individuals in China is relatively high in Shanghai. They acknowledge that using digital technology increases costs, but these costs are acceptable. Elderly individuals in Shanghai have relatively low concerns about privacy risks. They may believe in Chinese digital privacy laws or feel they have little privacy to be concerned about being stolen. This is inconsistent with past research, as privacy risks have

traditionally been believed to be one of the factors affecting people's use of technology (Lustgarten et al., 2020). Overall, they do not perceive these obstacles as significant.

Elderly individuals in Shanghai, China, do not perceive themselves as being restricted by society; they feel free to choose between digital and non-digital technologies according to their preferences. Like Generation Y, they also dislike artificial intelligence responses. Robot services lack emotions and cannot establish friendships with consumers, potentially leading to customer dissatisfaction and feeling undervalued (Blanche et al., 2020).

5.2.2 Research Hypothesis Findings

5.2.2.1 HBM model findings

Neither Generation Y nor Baby Boomers' perceived susceptibility to the pandemic (PSU) significantly affects perceived usefulness (PU) of new retail-related technologies (including instant retail, self-checkout, and e-commerce assistants). In the post-pandemic period, the public's perception of susceptibility to infectious diseases has not become a decisive factor in their assessment of the usefulness of digital technologies. This finding is in stark contrast to the results of studies during the early outbreak. In the early days of the COVID-19 outbreak, a large number of empirical studies showed that PSU was a key variable driving the public's adoption of health-related behaviours and digital health technologies (Kwok, 2020; Wei et al., 2020; Daragmeh et al., 2021; Puriwat & Tripopsakul, 2021). When faced with high uncertainty and health risks, people usually reduce risks by enhancing protective behaviours, such as turning to online shopping, contactless payment, and remote delivery services (Zhao et al., 2018; Gao et al., 2020).

This phenomenon can be attributed to risk habituation and information fatigue effects. Humans will gradually become less sensitive to long-standing risks and form a familiar cognitive state (Taylor, 2020), especially in the absence of new health crisis stimuli. Therefore, even if epidemics such as H1N1 or influenza A are still occurring, Generation Y and the elderly will not regard them as a motivation to change their shopping habits. This result is consistent with the dynamic model of risk perception proposed by Dryhurst et al. (2020), which believes that perceived threat is not a static variable, but is closely related to political context, media communication density, social memory and group sentiment.

This de-threat trend is more significant among Generation Y. First, compared with baby boomers, Generation Y has stronger information screening capabilities and diversified information sources. They can often quickly learn about the severity of the epidemic, the transmission path of mutant viruses, and changes in government policies through social media (Lissitsa & Kol, 2021). Second, Generation Y has higher health literacy and digital skills, which makes them more inclined to use self-assessment and subjective judgment when dealing with health risks, rather than relying on traditional perception indicators. Among the elderly, although the perceived severity (PSE) is high, the PSU path is not significant, indicating that they are not very concerned about whether they will be infected or have regarded the risk of infection as part of life. Liu (2023) pointed out that as epidemic prevention and control measures are relaxed, the elderly's demand for social participation and freedom of activity has increased rapidly, gradually weakening the restraining effect of health fear on their behaviour.

H1 (both Gen Y and Baby Boomer invalid assumption): *In the use of new retail e-commerce assistants, instant retail and self-checkout systems, perceived susceptibility*

to the pandemic ***not*** *affects people's judgments of the perceived usefulness of their technologies.*

This study did not find that perceived severity (PSE) had a significant impact on perceived usefulness (PU), whether in the Y generation or the Baby Boomers group. This result deviates from the core proposition of the Health Belief Model (HBM) early research that perceived threat affects behavioral choices (Rosenstock, 1974; Becker, 1979). In the post-epidemic period, health threats are not enough to become a common new retail perceived usefulness factor for people. In the early days of COVID-19, PSE was proven to effectively predict people's adoption of isolation, protection, and online consumption behaviors (Kim & Kim, 2020; Laato et al., 2020; Han et al., 2021; Hammood et al., 2023). However, this study found that its marginal effect significantly decreased in the framework of the impact of epidemic perception on the perceived effectiveness of digital retail systems. Although the perceived severity of the COVID-19 pandemic reached the level of agreement among the Y generation, it did not significantly affect their cognitive evaluation of instant retail, self-service checkout and other systems. This may suggest that technology acceptance decisions have shifted to areas dominated by utilitarian factors such as habit, convenience, and efficiency (Venkatesh et al., 2012).

During the peak period of COVID-19, the fluctuation of PSE can determine people's behavioral shifts, such as shifting from offline to online, and from manual services to unmanned technology (Wise, 2020). However, as the epidemic becomes normalized, vaccines are popularized, and social adaptation mechanisms are formed, the influence of PSE tends to weaken (WHO, 2023). As a group that has experienced the outbreak, recovery, and adaptation of the epidemic, the Y generation has normalized the threat

of the virus in its psychological model, and its focus has shifted to whether it saves time, whether it is easy to operate, and whether it conforms to the daily rhythm (Zhang et al., 2023). No significant path relationship between PSE and PU was found in the elderly group, which subverted the assumption in previous studies that the elderly are more sensitive to health threats and therefore rely more on preventive technologies (Chua et al., 2021)

After long-term lockdown and repeated information bombardment, the psychological threshold of the elderly to the epidemic has increased, that is, they take the disease lightly; second, the new retail system itself lacks effective communication in promoting health benefits. For example, self-checkout systems and instant delivery platforms did not emphasize the information advantages of reducing infection risks in their promotions, but instead focused on the use logic of saving time and avoiding queues. This omission has prevented PSE from activating users' cognitive paths to their health protection value (Wei et al., 2020). In the context of collectivism, diseases are often seen as a collective response rather than an object of individual self-help (Xu & Chen, 2021). This indicates that even if individuals subjectively recognize the severity of the epidemic, it may not necessarily translate into recognition of the health functions of digital retail systems.

H2 (both Gen Y and Baby Boomer invalid assumption): *In the use of new retail e-commerce assistants, online shopping and self-checkout systems, perceived severity to the pandemic* ***not*** *affects people's judgments of the perceived usefulness of their technologies.*

Perceived Health Benefit has been widely proven to have significant predictive power in the field of health behaviour decision-making (Becker, 1974; Champion & Skinner, 2008). This study did not find a path relationship in which PHB significantly affects PU (Perceived Usefulness) in the new retail context. Although the original design intention of new retail technologies, especially self-service checkout, instant retail and e-commerce assistants, can indirectly achieve the health goal of reducing the risk of infection, most users do not subjectively regard these technologies as health management tools, but rather as daily configurations for efficiency improvement and shopping convenience. This cognitive bias reflects the significant misalignment between technical intentions and user interpretations (Rogers, 2003), and also verifies the resocialization process of functional significance in technology adoption theory (Orlikowski, 1992). It is clear that today's findings differ significantly from those during the pandemic (Han et al., 2021; Puriwat, W., & Tripopsakul, 2021; Daragmeh et al., 2021).

The attitude of Generation Y towards PHB is uncertain. This generation generally has stronger self-immunity confidence, higher trust in the medical system, and the risk perception of the disease has significantly decreased in the later stage of the epidemic (Fan et al., 2023). Therefore, they do not equate new retail technology with a health protection barrier. They may pay more attention to whether the technology saves time, whether it is seamlessly integrated with social platforms, and its interactive attributes (Lissitsa & Kol, 2021). Baby Boomers often find it difficult to directly perceive the health benefits in the actual experience of using new retail systems. For example, many elderly people still think that self-service checkout is difficult to operate, instant retail involves packaging cleaning and logistics uncertainty, and AI e-commerce assistants

cannot replace face-to-face communication. These experiential feedbacks greatly weaken the weight of health benefits in cognitive models (Jokisch et al., 2020).

PHB may focus too much on macro benefits, such as reducing infection rates, and ignore perceptibility (Tang et al., 2022). In the early stage of the epidemic, people's demand for contactless technology was highly context-sensitive and emotionally driven, but after the post-epidemic life order gradually returned to normal, this type of technology gradually returned to domesticated technology, and thus could no longer serve as an urgent driving force for behavioural choices (Fischhoff, 2020). The study suggests the need for a more refined definition of its applicable scenarios. For example, national advocacy of its use will enhance the elderly's perception of technological health.

H3 (both Gen Y and Baby Boomer invalid assumption): *In the use of new retail e-commerce assistants, instant retail and self-checkout systems, perceived health benefits to the technologies* ***not*** *affect people's judgments of the perceived usefulness of their technologies.*

5.2.2.2 TORAOA model findings

Digital equipment have no significant effect on the perceived barriers of Generation Y users ($\beta = -0.084$, $p = 0.252$), but show a significant negative relationship in the Baby Boomers group ($\beta = -0.410$, $p < 0.001$). This result reveals the important implications of the generational differences in technology, that is, digital devices are still a key factor restricting their willingness and behavior to use technology in the middle-aged and elderly groups, but their influence has gradually been marginalized in the digital natives of Generation Y. This finding is in sharp contrast to van Dijk's (2005) device

gap theory, and also echoes the view of Venkatesh et al. (2012) that the facilitating condition dimension in the UTAUT model has deviations in applicability to different groups. Although the digital access rate of middle-aged and elderly people in some first-tier cities in China, such as Shanghai, has increased, there is still a gap between usage ability and cognitive confidence, which may lead to their relatively poor purchase of digital devices (Nistor et al., 2019).

Generation Y's dependence on device ownership has shown the characteristics of an implicit foundation. Smartphones, Pads and other devices are ubiquitous in their lives. From shopping, payment, navigation to health management, digital devices have long become an integral part of their daily work. Therefore, they are not sensitive to whether they have devices, but instead focus on experience optimization and platform stickiness during use. Therefore, the device itself no longer constitutes a decisive obstacle for Generation Y. This phenomenon also echoes the functional fade-out hypothesis proposed by Lissitsa and Kol (2021), that is, after technology develops to a certain degree of popularity, the marginal impact of its basic components will gradually fade away, and be replaced by advanced elements in behavioral motivation, such as interactive experience and personalized recommendations. Among the middle-aged and elderly population, the lack of equipment not only means the absence of the terminal, but also a disconnection between culture and information (Chen & Chan, 2014). This type of technology marginal population is easily excluded by the digital system due to equipment problems, resulting in cognitive islands and behavioral breaks.

H4 (Gen Y invalid assumption): In the use of new retail e-commerce assistants, instant retail and self-checkout systems, digital equipment not requires an impact on people's perceived barriers to the use of new retail technologies.

H4 (Baby Boomer Assumption is established): In the use of new retail e-commerce assistants, instant retail and self-checkout systems, digital equipment requires an **negative and significant** impact on people's perceived barriers to the use of new retail technologies.

The impact of perceived financial cost on perceived barriers is significantly positive in Generation Y ($\beta = 0.529$, $p < 0.001$), and is not significant in the Baby Boomers group ($\beta = 0.028$, $p = 0.053$), but close to significant. The mental accounting theory proposed by Thaler (1980) points out that consumers tend to classify expenses into necessary expenses and marginal expenses. Costs related to new retail, such as equipment costs, traffic expenses, additional fees for takeout, re-deductions due to operational errors in self-service checkout, platform service fees, etc., are all classified as non-essential expenses by many consumers. Especially in the current urban reality of China where price fluctuations and income anxiety are intertwined, when young groups (i.e. Generation Y) face multiple economic pressures such as mortgages, child support, and commuting, any additional usage costs are magnified as cognitive barriers. This also forms a mutual confirmation with the research results of Luarn and Lin (2015) on the impact of financial costs on the willingness to accept mobile commerce.

As pointed out by van Dijk (2020), the digital divide is not only reflected in whether technology is used, but also in the inequality of the cost of use. For groups with high frequency of contact with technology, Gen Y is more sensitive to the platform charging

mechanism, especially in applications such as instant retail (such as Dingdong Maicai, Meituan Flash Purchase), e-commerce assistants (such as Taobao AI customer service) and smart self-service checkout. The opaque charges or the superposition of service fees will form a strong psychological expenditure resistance. In the Baby Boomers group, the impact of financial costs tends to converge. This group is mostly retired people with relatively fixed income sources and are sensitive to prices, but their frequency of use is low and their understanding of the platform operation structure is shallow, which reduces their perception of financial traps. New retail platforms often optimize profit models by default payment, bundled packages, personalized premiums, etc., but such designs often deviate from the real needs of consumers, thus forming institutional barriers (Zuboff, 2019). The more types of tools Gen Y uses, the more obvious their perception.

H5 (Gen Y assumption is established): *In the use of new retail e-commerce assistants, instant retail and self-checkout systems, perceived financial cost has an positive and significant impact on people's perceived barriers to the use of new retail technologies.*

H5 (Baby Boomer invalid assumption): *In the use of new retail e-commerce assistants, instant retail and self-checkout systems, perceived financial cost has* ***no*** *impact on people's perceived barriers to the use of new retail technologies.*

In the Baby Boomers group, privacy risk (PR) has a significant positive impact on perceived barriers (PB) ($\beta = 0.397$, $p < 0.001$), while in Generation Y, this path did not reach statistical significance ($\beta = 0.206$, $p = 0.110$). Privacy risk is a key dimension in perceived risk theory, which represents an individual's concern that their personal information may be collected, abused, shared, sold, or leaked when using

technological products or services (Lim, 2022). Nissenbaum (2009) emphasized that privacy is not absolute control over information, but rather a judgment of the appropriateness of information flow that is closely related to the environment, relationships, and culture.

The performance of Generation Y is more complicated. Individuals know that there are privacy risks, but still actively hand over data in exchange for convenience or experience (Kokolakis, 2017). This means that privacy risks may not directly form barriers, but may be neutralized by technical proficiency. As Barnes (2006) pointed out, young users are accustomed to rapid migration between technology platforms and have stronger coping strategies for privacy risks (such as virtual identity, permission control, and data encryption), thereby reducing their psychological threat level. Zuboff (2019) pointed out that the coded obedience mechanism is widely present in the current platform capitalism, that is, the technology interface seems neutral, but its underlying logic is actually behavior induction and information capture.

For middle-aged and elderly people, system-recommended products, voice recognition, photo analysis and other behaviours are understood as being monitored rather than being served, which deepens their distrust. New retail technology extends digital monitoring to offline scenarios, such as camera recognition in the checkout area and behavior tracking of self-service machines, making data tracking behaviors that originally only existed on the Internet perceptible and visible, further amplifying the resistance of middle-aged and elderly people to privacy risks (Smith et al., 2020). They are not only worried about data collection, but also worried that every move they make is defined by algorithms.

H6 (Gen Y invalid assumption): *In the use of new retail e-commerce assistants, instant retail and self-checkout systems, privacy risk* ***not*** *impact on people's perceived barriers to the use of new retail technologies.*

H6 (Baby Boomer assumption is established): *In the use of new retail e-commerce assistants, instant retail and self-checkout systems, privacy risk* ***positive and significant*** *impact on people's perceived barriers to the use of new retail technologies.*

In the Baby Boomers group, perceived self-efficacy (PSEF) has a significant negative impact on perceived barriers (PB) (β = -0.175, p = 0.016), while in Generation Y, although the path direction is negative (β = 0.084), it does not reach statistical significance (p = 0.074). Self-efficacy is defined as an individual's self-judgment of his or her ability to successfully complete a task. It is not only a manifestation of technical knowledge, but also a cognitive belief: whether the individual believes that he or she can effectively operate in a technical context, handle difficulties, and overcome learning costs (Al-Abyadh et al., 2022).

In the elderly group (Baby Boomers), self-efficacy significantly affects perceived barriers, indicating that under the stimulation of high-efficacy beliefs, elderly users are more likely to cross various obstacles to using new retail technologies, such as interface operation difficulty, functional understanding barriers, and device trust anxiety. This is similar to previous studies on the elderly (Yu et al., 2022). The path of Generation Y users did not reach significance, which may reflect the phenomenon that skills have been internalized and confidence is not a bottleneck. For this group, self-efficacy has long become a basic quality. The use of technology is no longer limited by whether it can be used, but more by whether it is worth using and whether you are

willing to use it. This also explains why perceived self-efficacy has little effect on their perceived obstacles. This is a new discovery.

H7 (Gen Y invalid assumption): In the use of new retail e-commerce assistants, instant retail, and self-checkout systems, self-efficacy has **no** impact on people's perceived barriers to the use of new retail technologies.

H7 (Baby Boomer assumption is established): In the use of new retail e-commerce assistants, instant retail, and self-checkout systems, self-efficacy has an **negative and significant** impact on people's perceived barriers to the use of new retail technologies.

5.2.2.3 UTAUT model finding

The path coefficient between PB and PU for the Gen Y group is -0.160, which is not statistically significant, but negatively correlated in direction, indicating that some users still subjectively weaken their perception of the utility of technology due to obstacles. In contrast, the path coefficient of the Baby Boomer group is as high as -0.975, and is highly significant ($p < 0.001$), indicating that perceptual obstacles almost completely obliterate the perceived effectiveness of technology. This result is consistent with the technological oppression effect pointed out by Li et al. (2020): for the elderly group, when obstacles accumulate to a certain threshold, technology itself will no longer be seen as a tool, but will be transformed into a source of threat to their life stability.

When the investment required for system operation by elderly individuals, such as equipment investment, learning cost, cognitive anxiety, risk and threat, is too high, the positive values of convenience and efficiency promised by the technology itself are

perceived to be diluted or offset, resulting in a significant decline in their subjective utility evaluation. Telpaz et al. (2015) found that when faced with multiple obstacles, brain activation levels decreased significantly, making it impossible for humans to make long-term value assessments. For example, whether the system is designed to take into account key human factors such as vision, hand stability, and text size (Marston & Samuels, 2019). But Generation Y may be different. Nistor et al. (2019) discussed the moderating effect of digital literacy. When individuals have strong information screening, tool selection, and problem-solving abilities, the weakening effect of PB on PU is significantly reduced.

H8 (Gen Y invalid assumption): *In the use of new retail e-commerce assistants, instant retail and self-checkout systems, barriers perceived has* ***no*** *impact on people's perceived usefulness to the use of new retail technologies.*

H8 (Baby Boomer assumption is established): *In the use of new retail e-commerce assistants, instant retail and self-checkout systems, barriers perceived an* ***negative and significant*** *impact on people's perceived usefulness to the use of new retail technologies.*

As the core resistance to usage intention, perceived barriers have long been confirmed by many theoretical and empirical studies (Venkatesh et al., 2012; Al-Dmour et al., 2020). The results of this study show that PB has a significant negative impact on both Gen Y and Baby Boomer groups, with the path coefficient of Baby Boomers being -0.425 ($p < 0.001$) and that of Gen Y being -0.419 ($p < 0.001$), indicating that the barrier variable shows a consistent strong interference effect between the two generations, reinforcing the structural destructive effect of PB in the model.

Thaler & Sunstein's (2009) nudge theory points out that human decision-making is not completely rational, but is regulated by a series of psychological frictions. In the new retail context, PB is the embodiment of this friction, which reverses the user's cost-benefit trade-off model into a risk-averse mode, that is, as long as the barrier exceeds the psychological tolerance threshold, the intention to use will be frozen. Although Gen Y has high technical literacy and experience, their rating of e-commerce assistants (M = 2.025) is significantly lower than their acceptance of other technologies, indicating that when a particular technology triggers specific obstacles such as privacy anxiety, inconvenient operation or poor communication, their intention to use will be broken. When the obstacle node in a behavior path is too high, the entire action path is cut off (Telpaz et al., 2015). Although Gen Y has strong information acquisition ability, they also show distrust of technology when faced with privacy risks, algorithmic bias or digital discrimination (Lee et al., 2019).

Behavioral characteristics of Baby Boomers. They not only score higher on PB (PB M = 3.6), but also show significant inhibition of intention to use, especially for ITU_C and ITU_B. Among China's elderly users, some technologies are seen as mandatory products of government digital transformation rather than service tools (Xinhua, 2022), which leads to irrational emotions such as resistance, fatigue and even resentment. This coincides with the critique of technological colonialism (Zuboff, 2019) proposed in recent years, that is, when the technology promoted by enterprises or governments lacks user autonomy and choice, it is very easy to evolve into a tool of behavioral oppression. Although both groups recognize the negative effects of perceived barriers, their internal driving factors are different.

H9 (both Gen Y and Baby Boomer assumption is established): *In the use of new retail e-commerce assistants, instant retail and self-checkout systems, perceived barriers* ***negative and significant*** *impact on people's intention to the use of new retail technologies.*

Movement Restrictions (MR) have a significant positive impact on the intention to use (UI) of the Baby Boomer group (β=0.436, p<0.001), while the path for Generation Y is not significant (β=0.010, p=0.916). Movement restrictions constitute a situational strength variable, and its logic of action is different from that of traditional individual attitude variables. Meyer et al. (2014) pointed out that strong situational variables have overwhelming power and can temporarily interrupt or reconstruct individuals' existing behavioral tendencies. The average intention of the Baby Boomer group for instant retail technology is M=3.449, and the self-checkout system is M=3.437, which has shown a trend of behavioral shift. It shows that the formation of behavior is not driven by long-term cognitive construction, but activated by short-term situational changes (Lim, 2021). When physical ability is limited and it is impossible to take a taxi or shop, individuals will seek solutions outside the system to meet their basic functional needs (Morrison et al., 2021).

Although the Gen Y group faces time constraints such as taking care of the family and workplace pressure (Hassan et al., 2023), their intention to use instant retail (M=3.975) is significantly higher than that of the elderly, indicating that their adoption of new retail technologies is more due to active choices rather than passive shifts after restrictions, so the paths of MR and UI are not significant. This is particularly common in the later stages of the epidemic. When city lockdowns are lifted and travel freedom increases, abandoning online retail and returning to offline shopping is normal

behavior (Xinhua, 2023). Therefore, restrictions alone to promote use are not enough to achieve long-term technological behavior transfer. In this regard, the study found significant differences between the elderly and Generation Y.

H10 (Gen Y invalid assumption): *In the use of new retail e-commerce assistants, instant retail and self-checkout systems, movement restrictions has* ***no*** *impact on people's intention to use of new retail technologies.*

H10 (Baby Boomer assumption is established): *In the use of new retail e-commerce assistants, instant retail and self-checkout systems, movement restrictions has* ***positive and significant*** *impact on people's intention to use of new retail technologies.*

In the Generation Y group, the path of social influence (SI) to usage intention (UI) is not significant ($\beta = -0.177$, $p = 0.062$), nor in the Baby Boomer group ($\beta = 0.023$, $p = 0.304$). This result contrasts with the positive effects in many traditional studies (Venkatesh et al., 2003; Karahanna & Limayem, 2000). Although Generation Y is in a highly socialized information environment, its motivation to use new retail is not significantly affected. This may be because the technology usage behavior of this group is more independent and individualistic, and their own technical ability and experience are sufficient, and they no longer rely on external social references to form behavioral judgments (Katz et al., 2022).

Although the elderly are encouraged by their children or peers, they are still uneasy or afraid of technology, so the behavior is not activated in the end (Joa & Magsamen-Conrad, 2022); on the other hand, there is reverse social norm conflict, such as negative comments, failure cases or fear stories from peers, which will inhibit individuals (Cambridge Geriatric Neuroscience Lab, 2024). Zhou et al. (2020) pointed out that the

elderly often face cognitive gaps and psychological pressure when receiving information from their children and social platforms. For example, many children tend to force binding their parents to use certain apps (such as health codes and mobile payments), which in turn arouses disgust and resistance, making SI a negative incentive mechanism. The social influence here actually produces normative dissonance. This study encourages elderly users to participate spontaneously by observing others. Similar strategies have achieved significant results in the promotion of digital health (Barnes et al., 2021).

H11 (both Gen Y and Baby Boomer invalid assumption): *In the use of new retail e-commerce assistants, instant retail and self-checkout systems, social* ***not*** *influence an impact on people's intention to use of new retail technologies.*

In the Baby Boomer group, perceived usefulness (PU) significantly and positively affects usage intention (UI) ($\beta = 0.528$, $p < 0.001$), while in the Generation Y group, this path is not significant ($\beta = -0.036$, $p = 0.649$). This finding challenges the classic assumption in the traditional technology acceptance model (TAM) that PU plays a decisive role in behavioral intention (Davis, 1989). For many elderly users, new retail technologies (such as self-service checkout, instant retail, and AI assistants) represent an effective alternative to physical functional decline (such as mobility difficulties, queuing difficulties, and memory decline) (Lee et al., 2024). The perception that technology can complete tasks that were originally difficult for me constitutes the instrumental value in a cognitive sense that is, they believe that technology is not for improving efficiency, but for restoration and is a walking aid for daily life (Shin et al., 2023). Therefore, their interpretation of usefulness is deeply physiological and survival-oriented, resulting in a stable positive correlation path between PU and UI.

Generation Y itself already has high digital literacy and technological adaptability, and new retail operations such as self-service checkout, online shopping, and scanning and picking up goods have long become the norm in their lives. This means that the usefulness of technology has become a baseline expectation for them and no longer has sufficient persuasiveness to drive behavioral changes. This phenomenon can be called the perceived usefulness saturation effect (PU Saturation Effect): when the basic efficiency of technology has been fully absorbed, PU loses its behavioral guidance and is replaced by appeals to higher-level dimensions such as emotional value, interactive experience, and brand identity (Chiang et al., 2024). There is also another possibility that this study did not pay too much attention to the conventional perceived usefulness of technology, but rather from the perspective of obstacles and health, which led to Generation Y believing that it was ineffective.

H12 (Gen Y invalid assumption): *In the use of new retail e-commerce assistants, instant retail and self-checkout systems, perceived usefulness has no impact on people's intention to use of new retail technologies.*

H12 (Baby Boomer assumption is established): *In the use of new retail e-commerce assistants, instant retail and self-checkout systems, perceived usefulness has an* ***positive and significant*** *impact on people's intention to use of new retail technologies.*

Facilitating conditions have a statistically significant impact on the intention to use of the Gen Y group ($\beta = 0.189$, $p = 0.032$), but there is no significant path effect on the Baby Boomers group ($\beta = 0.004$, $p = 0.871$). This result shows that the influencing mechanism of convenience conditions may have a structural break between different generations. The perceived saturation phenomenon of Generation Y on convenience

conditions has become a key variable for the failure of its influencing path. In highly digital cities such as Shanghai, stable Wi-Fi, popular code scanning devices, and APP services available everywhere constitute the default structure of their daily lives, thus degenerating convenience conditions from motivational variables to background constants (Sun et al., 2022). Therefore, they cannot accept an environment without convenient conditions.

The elderly have lived in an era without technology for the past few decades and have relatively little resistance to Internet disruptions and face-to-face shopping and payment in supermarkets. This cognitive mechanism tends to regard convenient conditions as buffer resources and non-essential resources to offset the technical stress response caused by insufficient self-efficacy, comprehension barriers and situational complexity (Chen et al., 2023). They can give up and withdraw at any time. Whether the technology can be enabled and whether a shopping order can be successfully completed depends entirely on whether there is sufficient convenience support (Zhang et al., 2018). This kind of rhetoric is inappropriate for older people who have experienced a technology-free environment.

H13 (Gen Y assumption is established): *In the use of new retail e-commerce assistants, instant retail and self-checkout systems, facilitating conditions has an* ***positive and significant*** *impact on people's using behaviour of new retail technologies.*

H13 (Baby Boomer invalid assumption): *In the use of new retail e-commerce assistants, instant retail and self-checkout systems, facilitating conditions has* ***no*** *impact on people's using behaviour of new retail technologies.*

The data of this study show that UI has a statistically significant positive impact on UB for both Generation Y (β = 0.545, p = 0.000) and Baby Boomer (β = 0.937, p = 0.000) groups. This finding is consistent with the vast majority of studies on the use of digital technologies, especially new retail technologies (Wang et al., 2022; Pramudito et al., 2023). In other words, whether it is the younger generation of digital natives or the silver-haired population who were once regarded as technology resisters, when they form a clear intention to use, they are likely to convert it into actual use behaviour. The path from intention to behaviour is more intense in the Baby Boomer group. Seidler et al. (2010) pointed out that young people have higher neural conduction efficiency between the prefrontal cortex and the primary motor cortex, so they can activate the execution path more quickly after forming a behavioural plan.

The elderly are more likely to have intentions and behaviours disconnected. This cognitive delay is the neural basis of the common high intention, low behaviour phenomenon in the elderly group, such as health behaviours, digital payments, and smart device use (MIT AgeLab, 2023). But this is not true in this study. Unexamined factors such as operational anxiety, unfamiliarity with the interface, and a crisis of trust in technology can also cause a delay in behavioural transfer (Choi et al., 2020). Existing studies have repeatedly proven that this can weaken the conversion efficiency of UI to UB (Foroughi et al., 2019). These factors are not true in this study. This may be due to the combined influence of health factors and resistance factors that drive the intention to use and behaviour, technology use among older adults is largely dependent on the removal of restrictions.

H14 (both Gen Y and Baby Boomer assumption is established): *In the use of new retail e-commerce assistants, instant retail and self-checkout systems, intention to use*

*has an **positive and significant** impact on people's using behaviour of new retail technologies.*

Experience (E) has a statistically significant effect on usage behavior (UB) in the elderly group (β = 0.047, p = 0.049), but not in the Generation Y group (β = 0.145, p = 0.345). This finding reveals that there are structural differences in the technology behavior paths between generations. Literature points out that the elderly often have technophobia and avoidance tendency when facing emerging technologies, and positive past experiences help them reconstruct their trust path in technology (Kim, 2021). Haier et al. (2018)'s study confirmed through electroencephalogram that high-frequency technology exposure can form decision-making areas in the brains of the elderly. The results show that technology experience can effectively lower the cognitive threshold of usage behaviour.

In the Generation Y group, the insignificant predictive power of experience on usage behaviour shows that for young people who are already digital natives, technology experience is not a key variable for behaviour transformation. They have been in a highly digital environment since birth, and their sensitivity and acceptance of new technologies come from immersive daily structures rather than isolated technological experiences (Choi, 2020). This suggests that the limited impact of experience on Gen Y behaviour may be due to the fact that their behavioural inertia paths are embedded in their lifestyles. This study contradicts the findings of past experience (Chen et al., 2023; Li et al., 2023). The study further revealed that for elderly users, attention should be paid to experience construction mechanisms, such as increasing their frequency of use through repeated training, usage demonstrations, and simulated experiences.

H15 (Gen Y invalid assumption): *In the use of new retail e-commerce assistants, instant retail and self-checkout systems, experience has* ***no*** *impact on people's using behaviour of new retail technologies.*

H15 (Baby Boomer assumption is established): *In the use of new retail e-commerce assistants, instant retail and self-checkout systems, experience has an* ***positive and significant*** *impact on people's using behaviour of new retail technologies.*

5.2.2.4 Mediation effect analysis

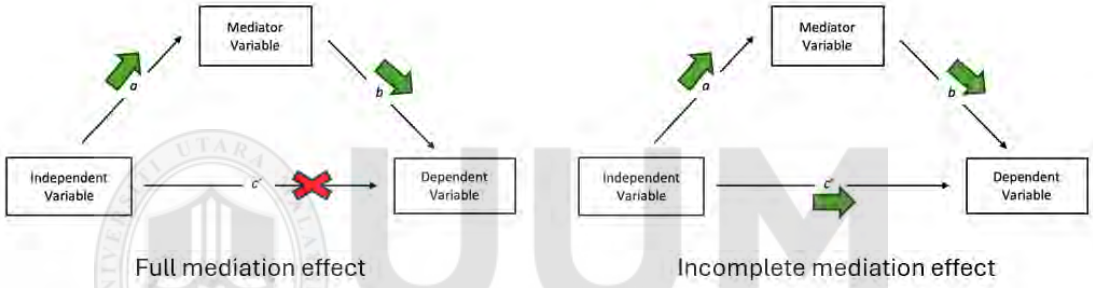


Figure 5.1 Full and incomplete mediators

The H16 hypothesis proposed in this study aims to explore whether perceived usefulness (PU) acts as a mediating variable to intervene in the path of perceived barriers (PB) on intention to use (UI). This model hypothesis is built on the intersection of the Technology Acceptance Model (TAM) and the Health Belief Model (HBM), emphasizing that behavioral intention is not simply driven by barriers or benefits, but is transmitted and transformed layer by layer through the mechanism of perceptual reconstruction, such as perceived barriers (Davis, 1989; Venkatesh et al., 2012). In the Baby Boomers group, the PB → PU path is significant (β = -0.975, p = 0.000), and the PU → UI path is also significant (β = 0.528, p = 0.000), which meets the basic

requirements of mediation analysis, that is, incomplete mediation (Figure 5.1). In the Generation Y group, PB → PU (β = -0.160, p = 0.311) and PU → UI (β = -0.036, p = 0.649) are not significant, indicating that perceived usefulness does not play a mediating role between the two.

For Baby Boomers, the reason why perceived usefulness can become a mediating variable is that it has the function of situational reappraisal mechanism. Existing studies (Kleijnen et al., 2009; Foroughi et al., 2019) have shown that when faced with technical barriers, elderly users do not directly form resistance, but decide whether to continue using it through a re-evaluation process, such as reviewing perceived usefulness. When it is found that this is a useful device or technology, even if the barriers are high, they will consider using it. But for Generation Y, the relationship between perceived usefulness of technology, perceived barriers and behavioral intention is complex. After all, almost all commonly used technologies are useful to a certain extent, and there are risks such as information leakage. Then the use of technology focuses on situational feedback in specific situations (Zhao et al., 2022), rather than the result of some deep thinking.

H16 (Gen Y invalid assumption): *In the use of new retail e-commerce assistants, instant retail and self-checkout systems, Perceived usefulness not as mediating variables between perceived barriers and using intention of new retail technologies.*

H16 (Baby Boomer assumption is established): *In the use of new retail e-commerce assistants, instant retail and self-checkout systems, Perceived usefulness as* ***incomplete*** *mediating variables between perceived barriers and using intention of new retail technologies.*

5.3 Research Contribution

5.3.1 Practical Contribution

5.3.1.1 Abandoning Digital Measures for Infectious Disease Prevention

Retailers may abandon or reduce digital policies related to infectious disease prevention. Gen Y and Baby Boomers refute the notion that new retail technologies significantly combat influenza A, influenza B, and pandemics. Health-related factors (PSU, PSE, PHB) do not enhance people's overall perception of the usefulness of mobile commerce assistants, instant retail, and self-checkout systems.

Therefore, when China experiences widespread epidemics, supermarkets need not alter their traditional retail and new retail patterns and distribution (for example, reducing manned lanes and increasing self-checkout lanes, encouraging instant retail while limiting store foot traffic).

5.3.1.2 Improving the Quality of Product Recommendations for the Elderly

Retailers can enhance the delivery of instant retail products tailored to meet the needs of the elderly. Surveys among Baby Boomers reveal that the elderly do not perceive new retail technologies as infringing upon consumer privacy, enabling supermarkets to amplify the delivery of instant retail products tailored to their needs. For instance, introducing dedicated sections for elderly products within instant retail channels can assist those lacking discernment in selecting high-quality products suitable for them, thereby reducing their shopping-related challenges. Unlike younger demographics, they typically have fewer secrets to hide, and the exposure of such secrets holds limited

influence and value. Thus, consumer information identification based on data mining techniques can sometimes be convenient.

5.3.1.3 Cancellation of Shanghai Elderly Retail App Development

The retail sector, primarily dominated by supermarkets, does not necessitate the creation of a separate app targeting the elderly. Various industries in China are dedicated to developing mobile technologies tailored for elderly users. In Shanghai, the elderly do not experience significant adverse effects on self-efficacy, as they believe in their ability to use these technologies. Cancelling the development of apps for the elderly is a cost-saving measure and a way to treat the elderly and other demographics equally.

5.3.1.4 Reducing Instant Retail Fees

Instant retail services should lower fee standards to increase Gen Y consumers' willingness to use them. Research findings indicate that financial costs, among other perceived barriers, influence Gen Y's willingness to use instant retail services. Therefore, businesses like Food Panda must consider the impact of delivery fees on consumers, and reducing delivery fees or product prices might be an ideal solution.

5.3.1.5 Reducing Artificial Intelligence Responses

The Gen Y and Baby Boomer consumer groups in China prefer human responses over artificial intelligence (AI) replies, resulting in a lower willingness to use such services. Retail enterprises should employ more online service personnel rather than online robots. This approach promises to offer consumers a better user experience.

5.3.2 Theoretical Contribution

5.3.2.1 Combining Promotion and Inhibition

This study adds to the most recent understanding of consumer behaviour and behavioural intentions by examining the effects of health factors (PSU, PSE, PHB) and barriers (DE, PSE, PR, PS) on consumers' perceived usefulness (PU) and willingness to use new retail technologies. It also explores the effect of the virus on the efficacy of retail technologies for consumers. In the context of retail technology, it discloses the psychological elements and driving forces impacting customer choice and adoption behaviour. Furthermore, the study considers social and physical restraints when substituting digital technology for human labour in smart cities.

5.3.2.2 Combining Gen Y and Baby Boomers

This study shows how Baby Boomers and Gen Y, two non-digitally native age groups, see and use modern retail technology. Retailers need to be aware of these distinctions to appropriately target and satisfy the requirements and preferences of various consumer groups with their products and tactics. China is now dealing with an ageing population crisis; thus, it is imperative to investigate the senior market. According to the STP marketing model (Segmentation, Targeting, Positioning), companies must determine which customer groups are their target markets and create strategies tailored to their unique requirements.

5.3.2.3 Combining UTAUT, TORAOA and HBM

This research is extensive, especially when it comes to the integration of theories. Combining these ideas offers a thorough framework for the future and advances

theoretical knowledge of the variables influencing the adoption of new retail technology.

This study is the first attempt to introduce the three core constructs of the health belief model, perceived susceptibility (PSU), perceived severity (PSE), and perceived health benefit (PHB), into the field of retail technology, aiming to explore whether consumers' perceived usefulness and willingness to adopt new retail technologies are affected by health considerations in the post-epidemic environment. The results show that the path significance of the model in technology decision-making is not established, suggesting that HBM does not have universal cross-domain explanatory power.

Although the UTAUT model emphasizes the predictive role of variables such as perceived usefulness (PU), convenience conditions (FC) and social influence (SI) on the willingness to use technology, this study found that these paths show significant differences among different generational groups: for example, perceived usefulness only has a significant positive impact on the Baby Boomer, but has no statistical significance for Generation Y; similarly, convenience conditions have a significant predictive power on the behaviour of the young group, but have no significant effect on the elderly group.

Starting from the background of social structural transformation during the pandemic, this study introduces mobility restrictions as a situational intensity variable that affects behavioral intention for the first time, and verifies that it has a significant impact on the willingness to use among the elderly ($\beta = 0.436$, $p < 0.001$). At the same time, the experience variable only has a significant effect on the actual use behavior of the

elderly, indicating that passive digitalization has become an important mechanism for the formation of digital behavior among the elderly during the pandemic. The introduction of these two variables not only strengthens the external adaptability of the UTAUT model in the context of the pandemic.

This study is the first to incorporate the key variables in TORAOA theory, namely, equipment, privacy risk, self-efficacy, and perceived financial risk, into the structural equation model and use them as the core dimensions that influence the construction of perceived barriers, which has been statistically significantly supported in the Baby Boomer group. This finding not only verifies the applicability of TORAOA in the Chinese context and the field of retail technology, but also further reveals the chain influence mechanism of each dimension of TORAOA on perceived usefulness and usage intention through quantitative paths.

In addition, this study goes beyond the original theoretical descriptive framework of TORAOA, endows it with structural explanatory power, and confirms for the first time its starting point role in the mediating role of perceived usefulness, reflecting the high compatibility and complementarity of TORAOA with UTAUT and HBM theories. Especially in the Baby Boomer group, the resistance factors revealed by TORAOA form a significant path dependence on behavioral outcomes. This finding responds to the criticism of the lack of theoretical integration motivation by external reviewers, and also provides a theoretical basis for the construction of a fusion resistance-acceptance behavior model in the future.

5.3.2.4 Combining Three New Retail Perspectives

The behavioural analysis in this study covers three areas: self-checkout systems, e-commerce assistants, and quick retail markets. This combination of these retail viewpoints has never happened before. There are similarities between the uses of digital technology in these three retail methods. However, they differ in how they communicate and conduct offline and online business. As a result, this is an excellent example of integration.

5.4 Insufficient Research

The study limits the respondents to 399 individuals aged in Gen Y (200) and Baby Boomers (199). Given the rapid growth and significant proportion of the elderly population in China, this study includes the elderly as part of the overall study population. However, this sample size and demographic limitation may not fully represent the diverse characteristics and preferences of the entire population.

5.4.1 Cross-Sectional Sampling Method

The study adopts a cross-sectional sampling method, which involves collecting data at a single point in time. While this approach provides a snapshot of the participants' perceptions and behaviours, it may not capture potential changes or provide a comprehensive understanding of long-term trends.

5.4.2 Non-Probability Judgment Sampling

The study utilises a non-probability judgment sampling method to select the target location. While this sampling method allows for convenience and accessibility, it may

introduce biases and limit the generalizability of the findings to other geographical locations or populations.

5.4.3 Ethical Considerations Limitation

The study adheres to ethical and legal requirements in China. The supervisor reviewed the questionnaire before distribution to ensure compliance. However, ethical considerations may vary across different cultural contexts, and the study's findings may be influenced by social desirability bias or other ethical challenges.

5.5 Future Research

In addition to transforming quantitative research into a mixed analysis based on qualitative and quantitative methods, researchers aim to consider new perspectives in the future. For instance, they intend to examine the views of elderly individuals regarding the addition of video or voice customer support services in the retail industry, as well as their opinions on robot delivery couriers for last-mile delivery. The former addresses the alleviation of typing and text-based communication barriers for the elderly. The latter addresses one of the current issues in China, where many delivery robots experience delivery delays due to problems such as yielding to pedestrians or obstacle avoidance.

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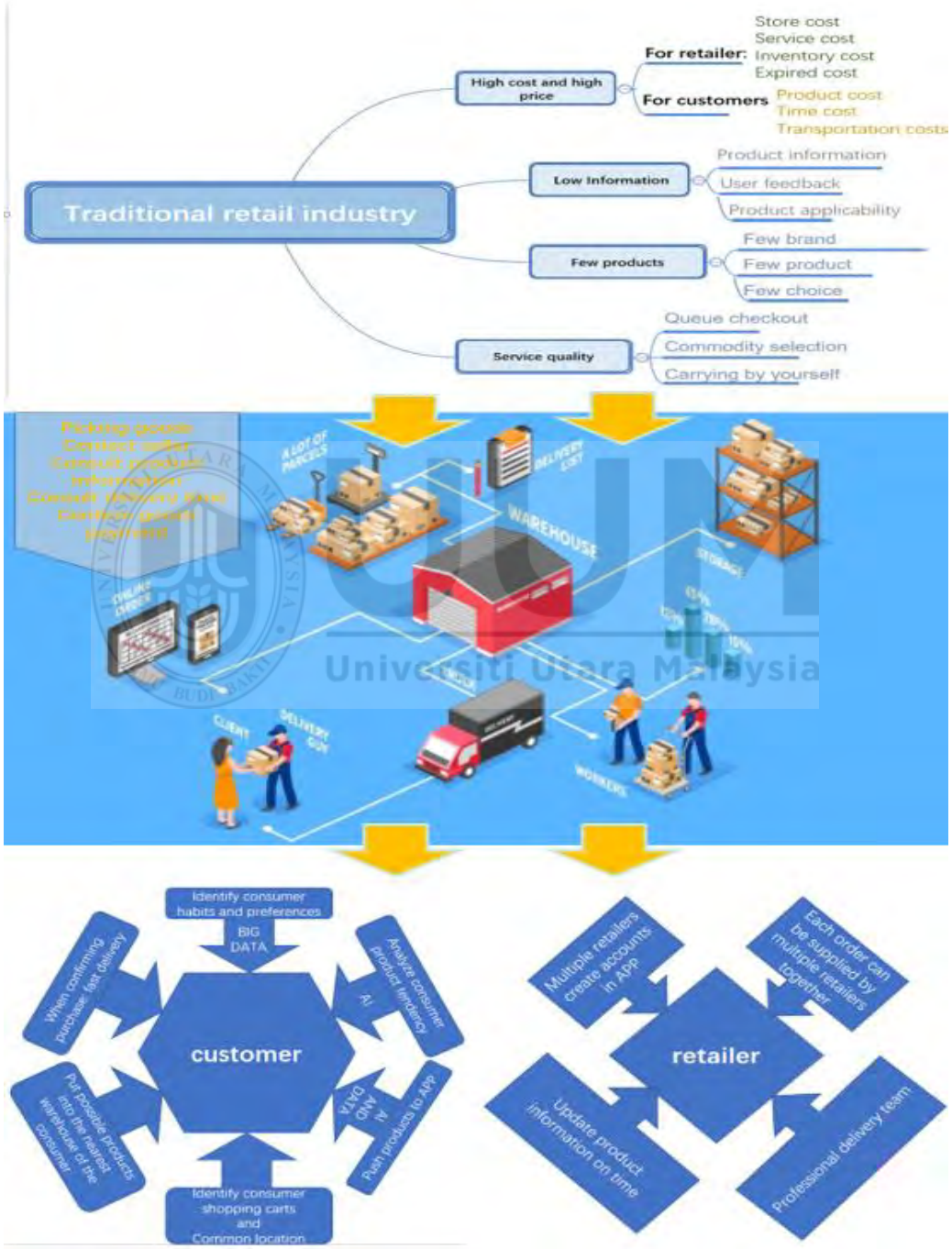
APPENDICES

Appendix A

Retail Changes A



Appendix B

Retail Changes B

The evolution of China retail industry

	Traditional Retail	Online Retail	New Retail
INFORMATION	Traditional retail has a little information technology. The main ones include: 1. Product Information: In traditional retail, consumers mostly choose products on their own. The consumer identifies whether the product meets the demand based on the instructions in the product packaging and the external performance of the product. 2. Word of mouth information: In traditional retail, it is difficult for people to purchase products through word of mouth. The main reason is word of mouth is based on verbal face to face communication. 3. Customer profile: When a customer needs help, the customer needs to inform his or her situation to the service personnel. This information will help service personnel to provide the right products and services. 4. User feedback: When we buy products, most of the product feedback we get comes from the service staff of the retail store. But the feedback is not necessarily true. (For example, when a retailer gives a higher commission and asks the salesperson to sell such a product as	Compared with the traditional retail industry, Internet retail has a specific improvement in the field of information technology. However, there are still drawbacks such as: × Customer profile × Product push information × Product specific style information	The new retail effectively combines traditional retail and Internet retailing and integrates and innovates on the following: ✓ product information ✓ Word of mouth information ✓ Logistics information ✓ customer feedback ✓ Customer profile（BIG DATA, AI） ✓ Product push information（AI） ✓ Product specific style information (3D, VR)

	quickly as possible, the salesperson may deceive the customer by exaggerating product features and making fake consumer feedback.)		
P R O D U C T S	In traditional retail, products are the primary factor in competition between retailers. It is also an important means of attracting consumers. However, in traditional retail there are still some problems relating with the product like: 1. Lack of product types (cost factors) 2. Product quality cannot be guaranteed (cost factor, moral factor) 3. Less choice of brand (cost factor) 4. High product price due to certain factors (rental, warehouse, product corruption, operating costs, etc.)	Compared to traditional retail, online retail has improved a lot as follows: ✓ Product quality ✓ Product brand ✓ Product price ✓ Product choice	The new retail perfectly inherits all the advantages of online retail. ✓ Product types ✓ Product quality ✓ Product brand ✓ Product price ✓ Product choice
L O G I S T I C	In traditional retail, logistics services are not included. Product normally self-selected and self-pickup. Delivery is only available for bulky and big size products. The time taken for delivery usually long.	The logistics service of the Internet retail industry improve significantly but sometimes still not reaching full potential. (In some situation customers need are very urgent but logistics takes about 2-7 days). ✓ Logistics distribution	The new retail offers consumers the nearest retailer based on the consumer's usual address and the location when the app is opened. This will ensure that consumers get the product in a short period of time. Backed by artificial intelligence (AI) can identify the

		service ✗ Delivery to the door ✓ Logistics insurance ✓ Delivery time operability ✗ Fast delivery ✓ Just in time	possibility of product purchases in consumer shopping carts. When the probability is greater than the set value, the item transfer is activated. Products will be moved from a remote warehouse to the nearest warehouse to the consumer. When the consumer starts purchasing the consumer may get the product in a very short period. In short, the customer enjoy the following: ✓ Delivery to the door ✓ Logistics insurance ✓ Delivery time operability ✓ Fast delivery ✓ Just in time
User friendly interface	Traditional retail stores do not have complex technology products and services.	The online retail enable user interface.	Simple upgrades of the previous online retail and optimizations are made in the online retail interface.
Service quality	Most of the traditional retail service provides consumers with basic equipment's (baskets, carts, money detectors, product price finder, etc.). Other customer service that available is after-sales replacement service and consultation with service personnel.	The quality of online retail services is better than the traditional type of retail industry. The variety of online retail products and brands are abundant. Product information is more comprehensive.	In the new retail, the information and the variety and quality of the products have been upgraded. The objective is to provide a push service tailored to the consumer needs. All of this meets the expectations of

		Meeting consumer expectations is possible. Online retail is convenient for consumers to shop.	consumers beyond imagination. In addition, transportation services may enhance significantly at the fastest speed; delivered to the door is within minutes; the operation interface is not only simple but also supports virtual reality (VR) visual function. These features make consumers feel excited and convenience at the same time.