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Reading between the lines of the second-hand e-commerce business in China: A study of consumer behaviour Xianyu second-hand platform

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READING BETWEEN THE LINES OF THE SECOND-HAND E-COMMERCE BUSINESS IN CHINA: A STUDY OF CONSUMER BEHAVIOUR XIANYU SECOND-HAND PLATFORM

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SINGAPORE MANAGEMENT UNIVERSITY
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Reading between the Lines of the Second-hand E-commerce Business in China: A Study of Consumer Behaviour Xianyu Second-hand Platform

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2023

I hereby declare that this DBA dissertation is my original work and it has been written by me in its entirety. I have duly acknowledged all the sources of information which have been used in this dissertation.

This DBA dissertation has also not been submitted for any degree in any university previously.

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Abstract

Second-hand transactions are gradually becoming an indispensable and significant form of the sharing economy; however, there is limited research on consumer behaviour in second-hand markets in an online environment. This dissertation aims to enrich the research in this area by analysing the impact of the characteristics of buyers, sellers, and products in second-hand markets on consumer purchasing intentions and behaviours. The study uses transaction data from Xianyu, China's largest C2C second-hand trading platform, to investigate the factors that influence consumers' choices between first-hand and second-hand trading platforms. It was found that consumers have a higher willingness to purchase well-known brands in second-hand platforms, and purchasing products with higher emotional value for consumers also increases the likelihood of choosing second-hand platforms. The study also examines the factors that influence consumer purchasing intentions in second-hand platforms and finds that seller characteristics, such as historical evaluation level and experience level, have a significant impact on buyers' purchasing intentions. However, this impact is not constant and is subject to modulation by buyer-related characteristics. Moreover, we extracted features such as emotions, motives, and strategies from the chat conversations between buyers and sellers using natural language processing (NLP) methods and validated that these features significantly affect the transaction outcomes. This research is an empirical study covering the entire process of online second-hand transactions, analyzing the influences of user and product characteristics, providing theory guidance and practical reference for the operation of second-hand trading platforms and consumer behaviour within these platforms.

Keywords: Second-hand transaction, platform selection, purchase intention, transaction prediction

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Throughout my DBA studies, I have been fortunate to meet many inspiring teachers and friends who have encouraged me and enriched my learning experience. I look forward to continuing our supportive relationships in the future.

As this five-year academic journey comes to a close, I express my deepest gratitude to all the teachers, classmates, and family members who have accompanied me. With your company, this journey of learning is full of fun.

Chapter 1 An Introduction to Second-hand Market

1.1 Background

1.1.1 Development of Second-Hand Economy and Sharing Economy

The online second-hand economy has experienced significant growth over the past few years. This is fueled by the increasing adoption of digital platforms, rising environmental awareness, and the desire for cost-effective consumption. This phenomenon has been shaped by, and has further contributed to, the broader sharing economy. The sharing economy, characterised by the peer-to-peer exchange of goods and services, has made it easier for individuals to connect and transact, allowing for the efficient redistribution of resources and the democratisation of access to a variety of products.

The global sharing economy market has rapidly expanded in recent years and is projected to generate roughly $335 billion by 2025 (Pcw, 2015). It has given us a new method to deal with the problems taken by capitalism and modern consumerism. In 2015, sharing economy-related platform generated nearly four billion euros and transactions of over 28 billion euros (Pcw, 2015). The sharing economy takes many forms, such as the home-sharing economy represented by Airbnb, which has profoundly changed the global hotel industry (Winkler R, 2015).

In China, the development of the sharing economy is also fast-growing. According to reports from "China Sharing Economy Development Report (2021)" (Cng, 2022), although the development of the sharing economy, which relies heavily on close interpersonal communication, has been negatively impacted by the COVID-19 pandemic, the scale of the sharing economy has still maintained a growth trajectory (shown in Figure 1-1). Furthermore, it is expected to maintain an economic growth rate of more than 10% in the next few years.

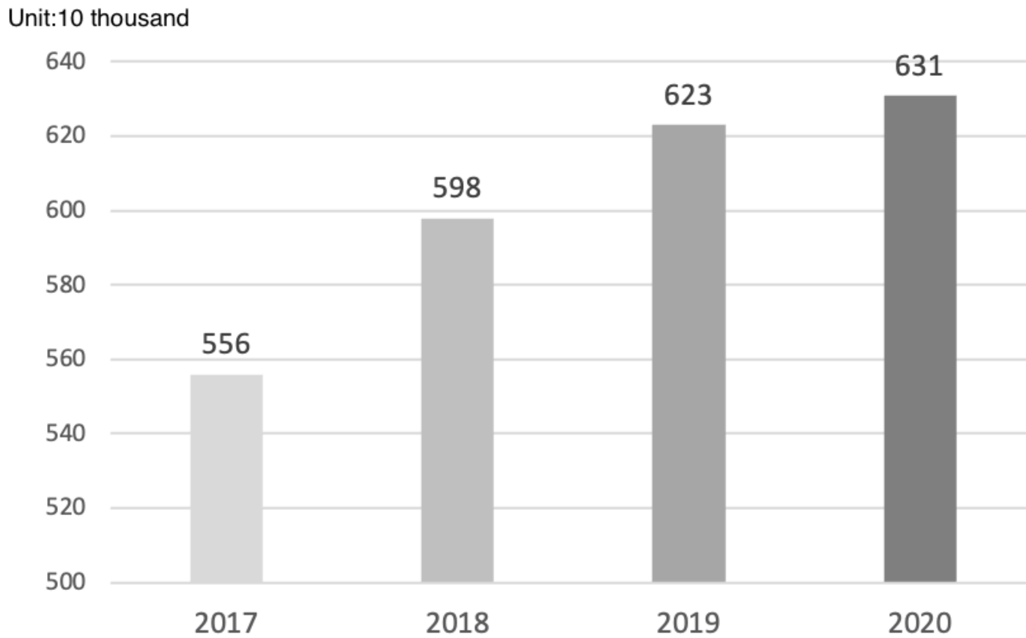


Figure 1-1 Sharing Economy Platform Employees in China from 2017 to 2020

The sharing economy and the online second-hand economy are intertwined, as they both encourage more sustainable and economically efficient ways of utilising resources. While the sharing economy primarily focuses on the temporary use of assets, such as ride-sharing or apartment rentals, the online second-hand economy emphasises the exchange of ownership. Both models challenge the traditional notion of ownership and promote the idea of access over possession, resulting in a more circular and sustainable approach to consumption. Now, the online second-hand economy has evolved from traditional brick-and-mortar thrift stores and classified ads to an ecosystem of digital platforms, such as eBay, Depop, and Poshmark, that facilitate the buying, selling, and renting of pre-owned goods. This development has been driven by technological advancements, such as mobile devices and secure payment systems, which have enabled seamless transactions and enhanced user experience.

In conclusion, the development of the online second-hand economy is an important aspect of the broader sharing economy, driven by advancements in technology and changing consumer values. As the sharing economy continues to grow, it is likely that the online second-hand economy will continue to expand and evolve, providing consumers with a more sustainable and cost-effective alternative to traditional consumption patterns.

1.1.2 Online Second-Hand Economy in China

The online second-hand market in China has experienced remarkable growth in recent years, driven by factors such as rapid digitalisation, a burgeoning middle class, and increasing environmental awareness. This expanding market has led to the emergence of numerous platforms and services that facilitate the buying, selling, and trading of pre-owned goods, ranging from clothing and electronics to automobiles and luxury items. Several platforms have emerged as key players in China's online second-hand market, including Xianyu and Zhuanzhuan. These platforms leverage advanced technologies, such as big data, artificial intelligence, and mobile applications, to provide a seamless user experience and ensure the authenticity and quality of the products being traded.

The predecessor of the Xianyu platform was Taobao's second-hand mall. By leveraging the substantial user base advantage brought by Taobao and Alipay within the same group, the Xianyu platform has rapidly developed and become China's largest C2C second-hand trading platform (as shown in Figure 1-2). Our research in this article is mainly based on the Xianyu second-hand platform, not only because it is the largest second-hand trading platform in China, but also because users of the Xianyu second-hand trading platform and the primary goods trading platform Taobao share a unified account. This allows us to analyze the different behaviors of the same group of users on both primary and second-hand trading platforms, providing excellent quasi-experimental conditions for our study.

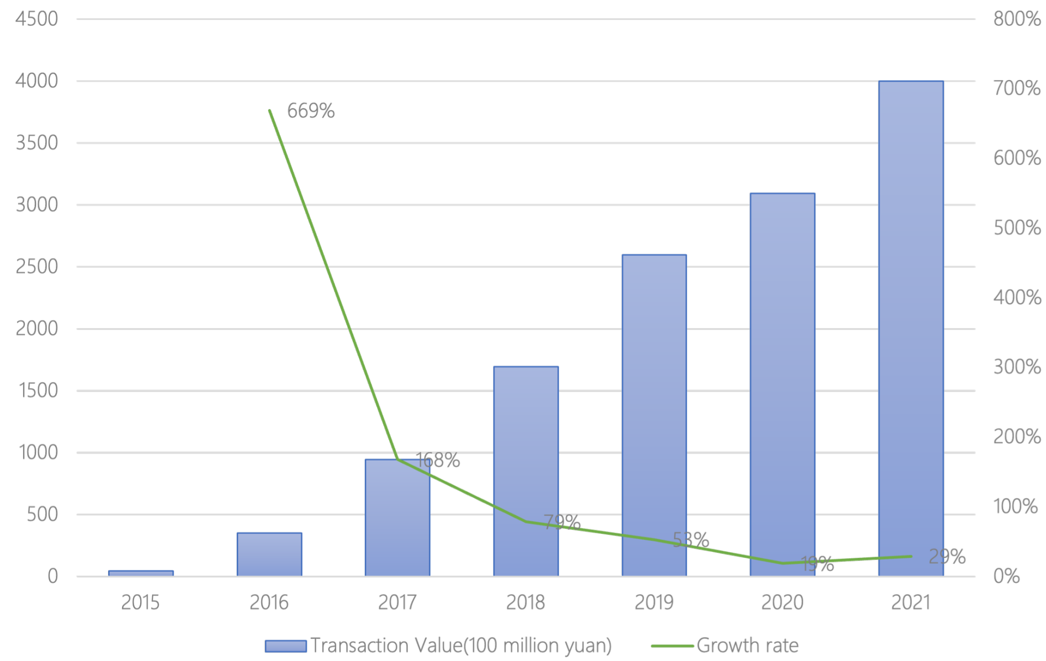


Figure 1-2 Transaction Amount Changes of Second-hand Market Scale

Today, Xianyu has grown into a super-large trading platform with over 100 million monthly active users, and it is the principal place for young Chinese people to conduct second-hand transactions. There are three main reasons for the fast development of the online second-hand market in China.

The Population of Consumerism

In the current social environment, consumerism has become popular with the development of the economy and the continuous enrichment of people's material life. At the same time, the development of e-commerce technologies and platforms has created some big online shopping platforms such as Taobao and JD.com. These online platforms have provided consumers with a convenient shopping experience and greatly stimulated their desire to consume. A large number of non-essential goods are bought in impulsive consumption by consumers. Daily necessities such as books and household appliances such as TVs may become idle items in this situation. On the other hand, the product's rapid iterative upgrade strategy has also greatly stimulated consumers' desire to purchase. At the same time, those "obsolete" goods will become idle items. However, these so-called inactive items are still usable and have the value of re-trading. In such an environment, the emergence and prosperity of the second-hand market will inevitably occur.

The Development of Application of Mobile Internet Technology

The development and application of mobile Internet technology are other indispensable factors for the rapid growth of the second-hand economy. In the traditional second-hand market, the number of sellers and commodities is minimal, and the choice of consumers is relatively tiny. Hence, the size of the second-hand market can only be maintained at a small scale. Online second-hand trading platforms like Xianyu and Zhuanzhuan in China are based on Internet technology. They use the online platform to match the idle items of a large number of users to others who need them. The platform construction and the popularisation of the mobile Internet have significantly increased the scale and matching efficiency of the online second-hand market. Millions of transactions can be done on the Xianyu platform daily, which is an astronomical figure compared to the traditional offline second-hand market.

The Support of the Chinese Government

Second-hand transaction satisfies consumers' consumption desires and people's material needs and reduces the waste of resources. It greatly conforms to the environmentally friendly policy (People's Daily, 2020). Hence, it is supported by the government of most countries in the world and is rapidly growing. This also includes the Chinese government's support for the development of the sharing economy, which has also become an important guarantee for the sustainable development of China's economy. The shared idle goods economy of Xianyu and car-sharing projects like DiDi, and shared housing projects like Xiaozhu have developed rapidly in recent years.

Under the influence of these three factors (shown in Figure 1-3), the concept of sharing economy is increasingly accepted by Chinese consumers. As China's largest online second-hand commodity trading platform, Xianyu has a bright future. Therefore, research on interesting issues, such as consumer behavior in the Xianyu platform, has important theoretical and practical significance.

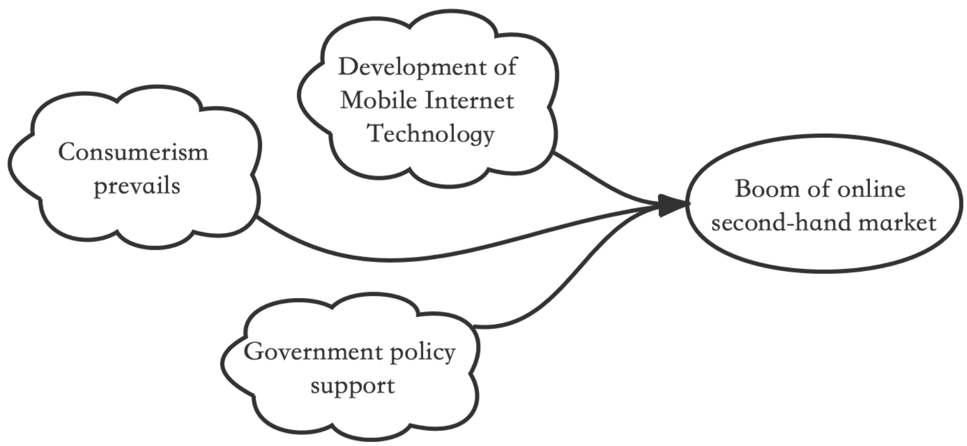


Figure 1-3 Why Online Second-hand Market Prosperity

1.2 Problem Statement

Although the sharing economy is rapidly developing and plays a more important role in the platform economy, many problems and areas still need to be urgently improved and solved. In this research, we mainly focus on three important issues: Firstly, the platform choice issue: We will investigate whether users are more inclined to choose traditional primary trading platforms or second-hand trading platforms when purchasing goods. Secondly, the purchasing intention of second-hand goods buyers: We will study the influencing factors affecting the purchasing intentions of second-hand goods consumers. Thirdly, the communication strategy issue: We will investigate the impact of factors such as emotions and strategies of both buyers and sellers in the communication process on the final transaction outcome.

1.2.1 Platform Choice Problem

Firstly, despite the prominence of second-hand trading platforms, a considerable number of consumers continue to prioritize offline shopping malls or online primary e-commerce platforms, such as Taobao, for their purchasing needs. Only a subset of consumers opts for platforms like Xianyu, influenced by factors such as economic considerations and entertainment value (Rohm & Swaminathan, 2004a; Wagner & Rudolph, 2010a). Although Xianyu offers exceptional idle commodity trading services, many consumers do not consider second-hand goods as their primary choice. Consequently, the circulation of idle goods requires further improvement, leaving many valuable items underutilided.

Our objective is to identify the determinants affecting consumer choice between platforms like Taobao, which focus on first-hand goods, and second-hand platforms such as Xianyu. For instance, we aim to understand if consumers with varying consumption lev- els exhibit different behaviours when purchasing diverse types of goods. The findings of this research will serve as a crucial theoretical foundation for comprehending consumer platform selection behaviour and enable targeted marketing strategies based on these insights.

1.2.2 Influencing Factors of Second-Hand Product Purchasing Intention

When consumers opt to purchase products within the second-hand market, they are confronted with the decision of selecting an item from a plethora of sellers. Although consumers may desire identical products from different sellers, second-hand items inherently exhibit non-homogeneity. Factors such as product condition, wear, seller descriptions, and seller characteristics contribute to these differences. Furthermore, information asymmetry is often prevalent in second-hand markets (Akerlof, 1978a), with sellers typically possessing more comprehensive and detailed information about the products. Under these circumstances, buyers may face the risk of being deceived by sellers.

In second-hand transactions, issues such as information asymmetry and the absence of third-party certification may foster distrust between parties, subsequently impeding the transaction process. This problem may be exacerbated in online environment, where buyers are unable to inspect the goods before completing the transaction. Consequently, online second-hand platforms often experience more pronounced trust issues, heightening risk perceptions for both buyers and sellers and resulting in a lower success rate for online second-hand transactions.

In an online second-hand market like Xianyu, buyers must evaluate various factors when selecting products, including product and seller information, to ensure satisfactory purchases. We want to find out the influencing factors that influence intention for consumers to purchase commodity in the online second-hand trading environment. Investigating this issue can facilitate smoother transactions between buyers and sellers on online platforms. For sellers, in particular, it offers insights into posting more appealing second-hand items on the Xianyu platform, thereby standardizing the product listing process within the second-hand marketplace. Encouraging the participation of high-credit users and promoting transparent product information contribute to the platform's healthy and sustainable development.

1.2.3 Chat Strategies in Online Second-Hand Transactions

Social attributes play a pivotal role in second-hand transactions (Rohm & Swaminathan, 2004b). Typically, buyers and sellers in these transactions engage in communication and negotiation to determine whether to finalise a transaction and at what price. The conversion rate of second-hand transactions is generally low, which significantly impacts the extent to which online second-hand transaction platforms can garner attention from mainstream consumers. The communication methods and strategies employed by buyers and sellers during this process, and their influence on the final transaction outcome, are of considerable interest to us.

Critical topics addressed by buyers and sellers during the negotiation include product details, authenticity, pricing, and logistical considerations. Deliberating these topics and the emotional states of both parties during the negotiation may serve as essential factors impacting the ultimate transaction result, which is the primary focus of this research. Lastly, price negotiation, as a crucial concern for both buyers and sellers, holds significant importance in determining the conclusion of a transaction. The manner in which bargaining occurs is also an area of interest to us. Examining these issues will facilitate a deeper understanding of the key concerns in the interactive process between buyers and sellers during online second-hand transactions. This understanding enables platforms to provide users with more effective transaction recommendations, ultimately promoting successful transactions.

The problem we discussed in this study is the complete conversion process of online second-hand transactions. This conversion process begins when consumers choose Xianyu to purchase products during the platform selection process, and the problem selection problem will be discussed in Chapter 3. Then, the process transforms into buyers being attracted by a specific second-hand product and show the intention of purchase, which will be studied in Chapter 4. Finally, we will analysis the impact factors to the completion of the transaction, which involves the strategies employed by both buyers and sellers during chat conversations, as well as the prediction of transaction outcomes, and will be discussed in detail in Chapter 5. The entire process is illustrated in Figure 1-4. Our research provides theoretical explanations for several problems in this process and practical suggestions for the operation of second-hand trading platforms and user behavior in the platforms.

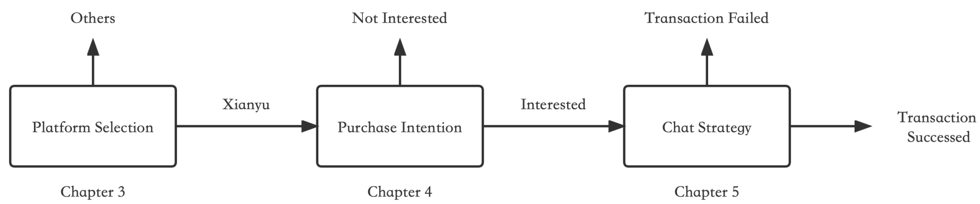


Figure 1-4 Conversion Process in Second-hand Transaction Research

Chapter 2 Literature Review

2.1 Consumer Behaviour in Second-Hand Consumer Market

Second-hand consumption refers to the act of purchasing a product that was previously owned by another individual (Roux & Guiot, 2008). This concept is frequently misconstrued with the acquisition of vintage items in everyday understanding. Vintage items are typically characterised as unique and genuine works (Gerval, 2008) that exemplify the stylistic tendencies of a specific time period. Although these antiquated items may have lost their functional value (Sihvonen & Turunen, 2016), they often embody the traits of an era, and their worth may appreciate over time (Sarial-Abi, Vohs, Hamilton, & Ulqinaku, 2017). Conversely, second-hand goods simply denote products previously possessed by others without consideration of their collectible value (Sarial-Abi et al., 2017; Cervellon, Carey, & Harms, 2012).

The second-hand market, a significant consumer market, has experienced over three centuries of evolution (Padmavathy, Swapana, & Paul, 2019). This market emerged and expanded during the 18th and 19th centuries, experienced a decline in popularity during the 20th century, and witnessed a resurgence in the 2000s (Weinstein, 2014). The second-hand market has become a powerful economic driver capable of fostering national economic growth (Thomas, 2003). Current research on second-hand shopping primarily investigates various determinants influencing consumers' offline second-hand purchasing behaviour. For instance, scholars have identified economic constraints and perceptions of price fairness as key factors motivating individuals to purchase second-hand items (Prieto & Caemmerer, 2013; Williams & Paddock, 2003). Additionally, buyers' environmental concerns and emotional attachments to collectible vintage items also contribute to their propensity to engage in second-hand shopping. Beyond affordability considerations, the distinctive experience and satisfaction derived from selecting a suitable second-hand product also encourage consumer participation in the second-hand market (Bardhi & Arnould, 2005; Lane, Horne, & Bicknell, 2009; Prieto & Caemmerer, 2013; Turunen & Leipämaa-Leskinen, 2015). A synthesis of prior research findings reveals four principal factors that promote second-hand consumption: economic motivations, entertainment motivations, critical motivations, and fashion motivations (Padmavathy et al., 2019).

2.1.1 Economic Motivation

Economic motivation primarily originates from consumers' price sensitivity or consciousness, encompassing aspects such as price satisfaction evaluation, the pursuit of fair pricing, and bargain-hunting behaviour (Guiot & Roux, 2010). These factors drive consumers to allocate their budgets across various expenditure categories, frequently resulting in buyers engaging in asset management and price assessment of purchasing behaviour. Such strategies can alleviate financial pressure and fulfill material requirements (Guiot & Roux, 2010). Economic motivations first appeared in studies investigating second-hand purchasing motivations that broadly emphasised the economic advantages of second-hand shopping (Williams & Paddock, 2003) and consumers' expectations of procuring less expensive products during negotiation processes (Gregson & Crewe, 1997; Stone, Horne, & Hibbert, 1996). Hamilton's research highlighted that acquiring second-hand goods represents a crucial approach for low-income consumers to reduce their financial burden and mitigate the conflict between economic strain and consumption desires (Hamilton, 2009).

Mukherjee et al. explored the behaviour and motivation of bottom-of-the-pyramid consumers purchasing second-hand goods (Mukherjee, Datta, & Paul, 2020). They emphasised that economic motivation is a paramount factor driving their consumption of second-hand items. Consumers with limited purchasing power seek affordable second-hand products to satisfy their desires, obtain social recognition by acquiring high brand-awareness items, and alleviate financial pressures, such as children's educational expenses. Furthermore, they noted that second-hand consumption may lead to compensatory consumption and elevated purchase intentions. This phenomenon may arise from the fundamental logic underlying certain individuals' consumer psychology. For instance, according to the social comparison theory proposed by Muller and Fayant, consumers tend to contrast their possessions with those of wealthier individuals (Muller & Fayant, 2010). They may even be willing to spend more money on products that satisfy their comparative psychology. It is worth noting that not only low-income consumers exhibit a strong enthusiasm for shopping. A study on ordinary consumers revealed that price discrimination encourages thrifty consumers to opt for second-hand goods due to their typically lower cost compared to new items (S. P. Anderson & Ginsburgh, 1994).

In conclusion, economic motivation is a key driver of second-hand consumption across various consumer segments, from low-income to ordinary consumers. This motivation stems from consumers' desire to manage their budgets effectively, find affordable products, and achieve social recognition. As a result, second-hand consumption enables individuals to address their financial pressures and material needs while potentially engaging in compensatory consumption behaviour.

2.1.2 Entertainment Motivation

Entertainment motivation in second-hand trading arises from three aspects: satisfaction derived from the product itself, the process of selecting a favored item among various products during the transaction, and the social attributes resulting from interactions with the seller throughout the transaction process. This entertainment motive constitutes a significant reason many second-hand goods buyers opt for this shopping channel (Belk, Sherry Jr, & Wallendorf, 1988; Guiot & Roux, 2010).

The shopping experience associated with second-hand goods transactions diverges from conventional purchasing channels. Consumers can browse, evaluate product characteristics and quality, and negotiate with sellers. These processes and experiences elicit unique interest among consumers enthusiastic about the second-hand market (Mathwick, Malhotra, & Rigdon, 2001). Furthermore, entertainment-driven second-hand purchases primarily concentrate on the distinctiveness and scarcity of second-hand items. These product attributes can gratify buyers' nostalgic sentiments and psychological needs for treasure hunting (Carrigan, Moraes, & McEachern, 2013; Guiot & Roux, 2010). For instance, Turunen et al. discovered in a study on women's consumption of second-hand luxury goods that buyers exhibit a keen interest in the attributes of antique treasures and venture capital, the repeatability of product selection, the authenticity of the transaction process, and the unique shopping experience (Turunen & Leipämaa-Leskinen, 2015).

A 2018 survey on second-hand luxury goods purchasing motivations identified nine primary reasons driving consumers to choose such products, with six factors relating to buyers' psychological decision-making processes. These factors include: differentiation, impressing others, attractiveness, being a luxury connoisseur, historical value and emotional connections to the past, and treasure hunting (Amatulli, Pino, De Angelis, & Cascio, 2018). Notably, second-hand luxury goods are not the only items that afford buyers an entertainment experience during the purchasing process. In a survey on second-hand furniture purchasing motivations, 25% of respondents reported choosing this option because they sought unique and distinctive products (Gullstrand Edbring, Lehner, & Mont, 2016). Entertainment motives ranked second only to economic motives as the primary driving force for second-hand goods purchases.

These motivations have given rise to second-hand shopping enthusiasts and collectors. For these shoppers passionate about hunting and discovering the unexpected, the pursuit of meaningful items during the second-hand buying process often serves as an identity marker (DeLong, Heinemann, & Reiley, 2005). According to DeLong et al.'s 2005 research findings, the second-hand market offers consumers a museum-like shopping experience, featuring tangible and experiential goods, fostering a sense of familiarity between buyers and sellers (DeLong et al., 2005). These experiences are identified as sources of entertainment motivation for second-hand consumers.

In summary, the entertainment motivation in second-hand consumption stems from the unique shopping experience, product satisfaction, and social interactions during transactions. This motivation not only drives consumers to purchase second-hand luxury goods but also applies to various second-hand products, such as furniture. The unique, museum-like shopping experience and the desire to find meaningful and scarce items to serve as identity markers are major drivers for second-hand shopping enthusiasts and collectors. This entertainment motivation, along with economic motivation, plays a significant role in consumers' decision-making processes when choosing second-hand goods.

2.1.3 Critical Motivation

Critical motivation represents the behavioural drive to choose second-hand products over traditional first-hand items for ethical reasons. For instance, consumers may opt for second-hand goods from an environmental protection perspective or to reject waste (Guiot & Roux, 2010; Pierce & Paulos, 2011). Such behaviour constitutes a spontaneous movement by consumers expressing their ideas of advocating waste rejection (Roux, 2006). Simultaneously, Brace-Govan and Binay argue that critically motivated second-hand goods consumers also demonstrate resistance to environmentally unfriendly large corporate chains (Brace-Govan & Binay, 2010). According to Tseng and Shuo-Chang's 2011 observations, increasing environmental challenges are altering people's views on environmental protection issues and significantly impacting their attitudes towards environmental management (Tseng & Tsai, 2011). Environmentally conscious consumers exhibit sustainable and socially responsible consumption behaviour through second-hand goods purchases (Carrigan et al., 2013).

Although Niinimaki's 2010 study on environmental issues and second-hand commodity consumption motivations revealed that environmental factors only constitute a portion of consumers' assessment of second-hand goods value, and may not be a decisive factor for purchasing such products (Niinimäki, 2010), a 2015 survey on second-hand furniture purchasing motivations found that 19% of respondents expressed concern about the environment and climate change. Furthermore, 14% of respondents indicated that environmental reasons were the primary driver for their used furniture purchases (Gullstrand Edbring et al., 2016). Although this proportion is not as high as economic motivation (47%), it ranks third among all motivations, indicating the critical motivation driven by environmental concerns is a significant factor in second-hand goods purchases.

A deeper analysis uncovers a connection between environmental concerns and individuals' propensity to buy used products. The literature describes this phenomenon as a human desire to balance attitudes and actions, thereby reducing cognitive dissonance (Whitmarsh & O'Neill, 2010). In reality, an ecological movement is emerging among consumer groups who express concern about excessive waste and environmentally detrimental market and economic practices, seeking to positively impact the environment and society through their actions. Purchasing second-hand goods is one of the essential symbols for expressing their opinions and implementing them into action (Brace-Govan & Binay, 2010; Cervellon et al., 2012; Ha-Brookshire & Hodges, 2009).

The critical motivation, driven by ethical and environmental considerations, plays a crucial role in the decision-making process for purchasing second-hand goods. Although it may not be as influential as economic motivation, it still holds a prominent position among various motivations. The critical motivation aligns with a growing ecological movement among consumers who aim to reduce waste and contribute positively to environmental and societal well-being. This motivation showcases the importance of understanding consumers' psychological needs and attitudes towards environmental issues when examining the factors influencing the second-hand goods market.

2.1.4 Fashion Motive

Fashion motivation is another significant driving force for purchasing second-hand goods, as proposed by Ferraro et al. 2016, primarily associated with consumers' desire for uniqueness and originality (Ferraro, Sands, & Brace-Govan, 2016). Buyers are more likely to engage in second-hand consumption when seeking a specific fashion style or aiming to create their distinctive fashion sense (DeLong et al., 2005; Reiley & DeLong, 2011). For instance, with second-hand clothing, there is a distinction between items purchased for fashion motives and those acquired for economic reasons (DeLong et al., 2005). Generally, the prices of these second-hand items will be higher than those of similar products in the primary market. Due to their age and scarcity, second-hand clothing and other fashion products with retro attributes are often perceived as more valuable (Cervellon et al., 2012). This situation also arises in designer works with retro attributes, particularly when such products embody the designer's unique style and the characteristics of a specific era.

Ferraro et al. highlighted that the primary motivations for buying second-hand goods still revolve around product value, entertainment, and critical thinking. However, since fashion-motivated consumer groups differ from other motivated consumers, this area remains a compelling topic for further exploration (Ferraro et al., 2016). Compare to other motivations, fashion motivation represents a distinct driving force for second-hand goods purchases, primarily driven by consumers' pursuit of individuality and originality. While product value, entertainment, and critical thinking are still the primary motivations, fashion motivation highlights the importance of understanding the diverse consumer groups and their motivations when examining the second-hand goods market. The uniqueness and scarcity of certain second-hand items add to their appeal, making them a popular choice among fashion-oriented consumers. As such, the fashion motivation deserves further attention and research to better comprehend its influence on the second-hand market.

2.2 Consumers in the Online Second-Hand Market

2.2.1 About Online Second-Hand Market

In the past decade, offline second-hand transactions have been more prevalent; however, with the development of the internet, the younger generation increasingly prefers to engage in online second-hand transactions (Liang & Xu, 2018). For example, Hvass et al., in their research on the sustainable fashion industry, identified that one of the reasons young people choose online shopping as a channel for second-hand transactions is the broader variety of products available on internet platforms compared to physical stores (Hvass, 2015). In contrast, research conducted during the rise of the internet in 2000 highlighted the elimination of time and space restrictions as one of the essential reasons for choosing online platforms, allowing people to shop anytime and anywhere (Reichheld, Markey Jr, & Hopton, 2000). Other factors specific to online second-hand trading platforms, such as the ability to conveniently query the functions and information of second-hand goods

(Resnick & Zeckhauser, 2002; Sihvonen & Turunen, 2016) and compare similar products (Sihvonen & Turunen, 2016), also contribute to people's preference for online platforms.

Second-hand e-commerce platforms generally serve as intermediaries in transactions, facilitating connections between buyers and sellers and allowing them to choose between online transactions or face-to-face offline transactions (Fernando, Sivakumaran, & Suganthi, 2018). However, this person-to-person second-hand transaction mode makes it challenging for sellers to establish a store brand effect and for buyers to develop unanimous praise and trust in a specific seller's store. Consequently, some emerging second-hand e-commerce companies invest heavily in promotions and operations to attract buyers to their stores but struggle to understand buyers' motivations for making purchases and repurchasing (Parguel, Lunardo, & Benoit-Moreau, 2017). Complex factors, such as varying living habits, shopping awareness, and consumption concepts, influence second-hand buyers' purchasing choices, making it difficult for them to form loyalty to specific sellers or second-hand shops (Joung & Park-Poaps, 2013; S. M. Lee & Lee, 2005; Yan, Bae, & Xu, 2015). In response, some professional second-hand sellers offer diverse services to retain existing customers and expand their user base.

The rapid development of second-hand shopping underscores the importance of research on the online second-hand market, particularly concerning people's motivations for online second-hand shopping and factors affecting online second-hand sales (Kestenbaum, 2017). Although studies in this field are still in their infancy, the increasing number of scientific literature related to online second-hand transactions signifies the importance and necessity of research in this domain. As the online second-hand market continues to evolve, comparing and summarising the findings from different research studies will be crucial in providing a comprehensive understanding of the motivations and factors influencing this burgeoning industry.

2.2.2 *Purchasing Motivations in Online First Hand Market*

To comprehend consumer motivations and behaviour in the second-hand e-commerce market, it is essential to examine existing research on conventional first-hand e-commerce environments. Several studies have explored various purchasing motivations in the context of online shopping.

Rohm and Swaminathan (2004) identified five distinct motivations for online shopping, including convenience, variety-seeking, reliable information acquisition, differentiated shopping experiences, and social interaction (Rohm & Swaminathan, 2004c). Wagner and Rudolph (2010) expanded upon these findings by proposing a three-tiered model of shopping motivation, consisting of purpose-fulfillment, activity-fulfillment, and demand-fulfillment (Wagner & Rudolph, 2010b). Purpose-fulfillment relates to the satisfaction consumers experience when acquiring desired items through an online platform, while activity-fulfillment represents the pleasure derived from satisfying shopping desires and obtaining cost-effective products. Demand-fulfillment, on the other hand, captures the convenience afforded by online shopping.

Price is another influential factor in online purchasing decisions, as evidenced by studies conducted by Kim and Lennon, which highlight its critical impact on consumers' purchase intentions (J. Kim & Lennon, 2013; Wolfinbarger & Gilly, 2001). The vast selection and comparability of products offered by online platforms are also significant drivers of consumer choice, as demonstrated by Park et al. (S. Ha & Stoel, 2009; E. J. Park, Kim, Funches, & Foxx, 2012).

Similar to traditional market channels, hedonic shopping value (derived from the enjoyment of shopping) and utilitarian shopping value (focused on product functionality and cost performance) serve as primary motivators for online purchasing intentions (Peng & Kim, 2014). Environmental stimuli, such as website design and functionality, play a role as well. Pragmatic and minimalist consumers are more likely to gravitate towards online shopping due to the convenience it provides (Chiu, Chang, Cheng, & Fang, 2009; Gong, Stump, & Maddox, 2013).

By comparing the motivations for online and offline purchases, it becomes evident that consumer motivations on second-hand e-commerce platforms may differ from those in traditional second-hand markets. However, further research is needed to establish the unique motivating factors driving second-hand online purchases and understand how they influence consumer behaviour in this rapidly evolving market.

2.2.3 *Purchasing Motivations in Online Second-Hand Market*

In comparison to traditional second-hand market shopping motivations, online second-hand transactions do share some similarities, such as seeking affordable items and acquiring unique products. However, there are numerous distinctions between the two (Parguel et al., 2017; Ferraro et al., 2016; Xu, Chen, Burman, & Zhao, 2014). For instance, consumers who value socialising with sellers might opt for offline flea markets over online platforms.

Economic motivation remains a key driver in the online second-hand market, with consumer behaviour on e-commerce platforms largely mirroring that in traditional second-hand markets (Padmavathy et al., 2019). Consumers evaluate product prices and value, paying reasonable amounts without overspending. While environmental considerations have been a significant motivation in traditional second-hand markets, younger consumers who typically prefer online platforms—focus on purchasing branded or higher-quality products at lower prices to fulfill their shopping desires, rather than prioritising environmental concerns (Xu et al., 2014; Edbring, Lehner, & Mont, 2016). Furthermore, second-hand e-commerce platforms generally operate as commercial entities rather than non-profit organizations focused on environmental protection (Parguel et al., 2017). As a result, Joung and Park-Poaps argue that there is no direct link between buying and reselling second-hand goods and environmental protection (Joung & Park-Poaps, 2013).

Convenience is an essential differentiating factor between online and traditional second-hand markets. The information search functions provided by online platforms reduce the learning curve for new users and facilitate more efficient transactions (Khare, Khare, & Singh, 2012; Rohm & Swaminathan, 2004c). This convenience, which saves users time and energy, encourages them to select online platforms over offline alternatives. Online intermediaries allow consumers to quickly locate desired products and complete transactions anytime, anywhere (Kollmann, Kuckertz, & Kayser, 2012). The information search function also enables users to compare and assess different second-hand products without physically visiting multiple locations, saving time and energy while making it easier to find suitable items. This efficiency, combined with other features, strengthens the convenience characteristics of online second-hand platforms (Khare et al., 2012), leading to an increasing number of consumers opting for online second-hand markets due to the convenience factor.

Overall, while online second-hand markets share some common motivations with traditional second-hand markets, such as affordability and unique product acquisition, there are notable differences in consumer behaviour and market characteristics (Parguel et al., 2017; Ferraro et al., 2016; Xu et al., 2014). Economic motivation remains a significant factor in both markets, but environmental concerns are less prominent among younger, online-oriented consumers (Xu et al., 2014; Edbring et al., 2016). Additionally, second-hand e-commerce platforms primarily operate as commercial entities, further diminishing the direct link between second-hand transactions and environmental protection (Parguel et al., 2017; Joung & Park-Poaps, 2013). The current state of research highlights the unique dynamics of online second-hand markets and their impact on consumer behaviour. Future studies should continue to explore these differences and investigate strategies to enhance the online second-hand shopping experience while addressing potential environmental and social concerns.

2.2.4 *Factors Affecting the Online Second-Hand Market Transactions*

There are many factors that affect the success of second-hand transactions on online platforms. In addition to consumers' own shopping motivations, buyers' and sellers' perception of the value of goods (Babin, Darden, & Griffin, 1994), the role of second-hand trading platforms (Luo, Wang, Zhang, Niu, & Tu, 2020), and both parties' perceptions of risks will all affect the occurrence of transactions (Ba & Pavlou, 2002).

Value Perception of the Product

As previously discussed, economic motivation is a vital and critical factor influencing purchasing decisions in both traditional and online second-hand markets. However, assessing the value of commodities in these markets is challenging due to the information asymmetry between buyers and sellers, resulting in unequal positions during transactions. Generally, sellers possess more knowledge about the product, giving them an information advantage. However, they may not accurately evaluate an item's value if they lack knowledge of the current second-hand market. Simultaneously, professional buyers active on platforms can obtain more pricing information. Regardless, information asymmetry can impact value perception for both parties, leading to adverse selection problems that hinder smooth transactions (Z. Li, Ji, & Tong, 2013). In traditional second-hand markets, the "lemons" problem often arises due to information asymmetry (Akerlof, 1978b), with adverse selection resulting in "bad money driving out good money."

The impact of second-hand e-commerce platforms on information asymmetry remains inconclusive. On one hand, these platforms offer an extensive range of second-hand commodities, enabling buyers and sellers to easily compare historical sales data and similar products, which facilitates preliminary value estimations (S. Ha & Stoel, 2009; E. J. Park et al., 2012). On the other hand, unless offline transactions are conducted, comprehensive assessments of second-hand goods' quality and condition are difficult for buyers and sellers. To address these challenges, some researchers suggest employing machine learning technology to provide objective value estimations for second-hand products. This can be achieved by utilising text description analysis, image analysis, and other big data techniques, ultimately promoting fair communication between buyers and sellers.

Current research highlights the significance of economic motivation in both traditional and online second-hand markets and the challenges associated with assessing commodity value due to information asymmetry (Z. Li et al., 2013; Akerlof, 1978b). Second-hand e-commerce platforms offer advantages such as extensive product range and easy access to historical sales data, facilitating preliminary value estimations (S. Ha & Stoel, 2009; E. J. Park et al., 2012). However, comprehensively assessing the quality and condition of second-hand goods remains difficult, which may impact the transaction experience. Some researchers propose using machine learning technology and big data techniques to address these challenges and foster fair communication between buyers and sellers. Further exploration of these approaches and their effectiveness in reducing information asymmetry and improving transaction experiences is warranted.

Platform Function

The emphasis consumers place on security and privacy protection is crucial for promoting online second-hand transactions. Security pertains to the perceived safety and reliability during the shopping process, while privacy protection involves safeguarding buyers' information throughout the transaction (Cheng, Yang, Chen,

& Chen, 2014). Consequently, protecting private information, such as transaction details and financial data, is a vital factor in determining the success of online second-hand transactions (Cheng et al., 2014). In this regard, assessing the quality of a second-hand e-commerce platform becomes essential.

Zeithaml et al. (2000) identified several key indicators for evaluating the quality of e-commerce platforms, including effective product inquiry, page browsing, shopping, and consultation capabilities (Zeithaml, Parasuraman, & Malhotra, 2000). Surjadjaja et al. (2003) described e-commerce as an entity that provides customers with products or services linked to pre-sales, transactions, and after-sales support via e-commerce shopping platforms (Surjadjaja, Ghosh, & Antony, 2003). Studies on second-hand e-commerce platforms have highlighted after-sales protection as a major concern, as buyers and sellers have unequal understanding of product condition and functionality, potentially resulting in buyer deception. Insufficient platform supervision can lead to frequent occurrences of such situations, consequently dampening consumer enthusiasm for second-hand e-commerce platforms.

Risk perception for users on second-hand e-commerce platforms primarily stems from distrust of transaction partners. Establishing trust is a common challenge for these platforms, as they lack the brand endorsement present on first-hand e-commerce platforms. Platforms that fail to address trust issues will struggle to attract a large user base. According to social capital theory, members within high-quality social networks perceive lower risks and stronger trust within the group (S. Li, Modi, Wu, Chen, & Nguyen, 2019; T. Wang, Yeh, Chen, & Tsydypov, 2016; Luo, Zhang, Hu, & Wang, 2016). As e-commerce platforms continue to grow rapidly, researchers are increasingly examining the factors influencing user trust in online environments. Chang et al. (2017) compared users' trust in social internet services provided by Facebook and LinkedIn, finding that social media's social influence enhances users' trust in these services (Chang, Liu, & Shen, 2017). Lu et al. (2010) determined that familiarity with the platform, perceived similarity, and structural stability are essential prerequisites for trust (Y. Lu, Zhao, & Wang, 2010).

China's largest second-hand trading platform, Xianyu, features two community models: one based on geographical location and another on interest type. Within these communities, members establish trust (L.-C. Hsu & Wang, 2008) by sharing common hobbies and values. Communication and interaction among community members can reduce transactional uncertainty and information asymmetry, greatly enhancing consumers' ability to predict the value of goods they buy and sell (Bao, Li, Shen, & Hou, 2016). Some studies have suggested that the quality of virtual communities and platforms significantly affects users' perceived trust (Luo et al., 2020).

In summary, security and privacy protection play a pivotal role in promoting online second-hand transactions. Evaluating the quality of second-hand e-commerce platforms is crucial, with after-sales protection being a significant concern. Trust is a common challenge for these platforms, and addressing this issue is vital for attracting and retaining users. Research suggests that familiarity with the platform, social influence, and high-quality virtual communities can foster trust, ultimately enhancing the overall user experience in online second-hand marketplaces.

Perceived Risk

In the realm of online transactions, consumers face various risk perceptions, which are inherent in both first-hand and second-hand online shopping processes. These risks may include payment safety, personal data security, product information scarcity, satisfaction, product quality, and after-sales protection (Paynter & Lim, 2001). Lee and Tan argue that the significant differences and increased complexity between online and traditional shopping can lead to heightened anxiety for consumers, fearing a loss of their rights and interests (K. S. Lee & Tan, 2003). Consequently, the online shopping environment is considered riskier and less trustworthy (Laroche, Yang, McDougall, & Bergeron, 2005), even being characterised as a risky activity (Almousa, 2011).

Although online shopping can offer cost-saving benefits, insufficient information and the inability to physically assess products may result in consumer dissatisfaction and financial losses (Featherman & Pavlou, 2003). These risks are amplified in the second-hand market due to the increased information asymmetry, potentially leading to purchases that deviate from sellers' descriptions and buyers' expectations. This, in turn, can result in negative shopping experiences and financial losses. Furthermore, unmet expectations can cause significant frustration and dissatisfaction among consumers, possibly making them feel disrespected (Ueltschy, Krampf, & Yannopoulos, 2004).

We can see that understanding and addressing the risk perceptions associated with online shopping, particularly in second-hand transactions, is essential to enhance consumer trust and satisfaction. A comprehensive approach to reducing information asymmetry, ensuring data privacy, and improving after-sales protection will contribute to a more positive and secure online shopping experience for consumers.

2.3 Perceived Value

Customer perceived value is a critical concept in modern marketing research, as it defines the key attributes of a product or service that appeals to customers and drives their interest (Z. Chen & Dubinsky, 2003). This value perception significantly impacts customer attitudes (Izquierdo-Yusta, Olarte-Pascual, & Reinares-Lara, 2015), satisfaction (Zboja, Laird, & Bouchet, 2016), loyalty (Kuikka &

Laukkanen, 2012), and purchase intentions (J.-J. Wang, Wang, & Wang, 2018). In value creation, customers act as both consumers and co-producers, playing an increasingly vital role in shaping brand and product values in the digital environment (Tomičić Furjan, Tomičić-Pupek, & Pihir, 2020; Rekettye & Rekettye Jr, 2019). As customer requirements and value awareness rise, capturing and analysing the essence of customer-perceived value becomes essential for businesses to remain competitive (Leroi-Werelds, Streukens, Brady, & Swinnen, 2014; Pham, Tran, Misra, Maskeliūnas, & Damaševičius, 2018).

2.3.1 Concept of Perceived Value

analysing and studying customer perceived value has become a popular approach for business managers and marketing researchers in the current market environment (Pham et al., 2018; Silva et al., 2018). Consumers seek value maximisation, evaluating and measuring the difference between revenue and cost (Kotler & Turner, 1997). They form value expectations and base their purchase decisions on whether the product's value aligns with these expectations. If the product's actual value exceeds the expected value, consumers are satisfied and more likely to repurchase. Conversely, if the actual value falls short of expectations, consumer satisfaction and repurchase probability decrease.

Perceived value is a subjective measure based on consumer experiences and is not static (J. C. Anderson, Jain, & Chintagunta, 1992; S. J. Kim, Wang, Maslowska, & Malthouse, 2016). Researchers must consider the current customer value perception and its changes over time, as the relationship between businesses and consumers evolves with market conditions.

In conclusion, current literature emphasises the significance of customer perceived value in driving consumer behaviour and maintaining business competitiveness. The dynamic nature of perceived value and its impact on consumer satisfaction, loyalty, and repurchase intentions warrant further exploration. analysing and understanding the components of customer perceived value and improving it is key to gaining a sustainable competitive advantage in the ever-changing market landscape.

2.3.2 Composition of Perceived Value

In common understanding, various dimensions of customer perceived value influence consumers' value perception and affect its change (Ulaga, 2001). Despite ongoing research, a consensus regarding the factors that affect customer perceived value and the sources that constitute it has not been reached. Early studies primarily focused on two factors influencing consumer value perception: quality and price. For instance, Bazel and Gail contended that product quality and price interact to determine customer perceived value. Subsequent researchers proposed multidimensional models to analyse consumer value perception in different consumption scenarios and product types (Silva et al., 2018).

With the rise of online shopping, consumer preferences have shifted from traditional shopping methods. This change has led to differences in perceived value due to variations in time, energy, and other costs associated with online shopping. Additionally, the content and quality of services provided in the online environment differ significantly from traditional shopping, further influencing perceived value (Chiu, Wang, Fang, & Huang, 2014; Naeem et al., 2015; Karjaluoto, Shaikh, Saarijärvi, & Saraniemi, 2019).

A review of existing studies reveals several common features. Most scholars agree that customer perceived value's core lies in the trade-off between perceived benefits and perceived losses, while some argue that perceived value solely encompasses perceived benefits. Importantly, the concept has evolved over time, with perceived benefits and perceived losses becoming more comprehensive. Customer perceived value, which is closely related to product or service usage, is generated under specific conditions. The quality-to-price ratio is a common value assessment method, but the overall evaluation is not solely based on these factors.

Previous studies have demonstrated that multiple types of value jointly determine consumers' final value perception, including product functional value, product social value, and emotional product value. Changes in these values can impact purchasing decisions. The functional value can be further divided into quality and price dimensions, resulting in three major dimensions (functional product value, product social value, and emotional product value) and four sub-dimensions (emotional, social, price, and performance/quality) (Sweeney & Soutar, 2001). However, the increasing prevalence of risk problems, such as information inconsistency in the internet environment, has led some consumers to incorporate risk perception into their perceived value, especially in the context of second-hand consumption, where risk perception is even more crucial.

Product Functional Value

In Jagdish's article exploring consumer decision-making, he posits that multiple value dimensions, including functional, emotional, and social value, contribute to the process, with functional value serving as the most fundamental driving force (Sheth, Newman, & Gross, 1991). Within the product functional value dimension, consumers primarily consider aspects such as quality, functionality, practicality, and cost-effectiveness of products or services, typically focusing on their own interests rather than those of others (Holbrook, 2006). This assumption aligns with basic economic theory and is widely accepted under the notion of rational economic actors.

Consequently, the functional value of a product represents the most fundamental dimension in value perception. In subsequent studies, researchers developed more comprehensive models to explain consumer behaviour, considering the influence of functional product value. In the Cognitive Affect Model, scholars regard consumers' perceptions of product functionality and quality as cognitive responses that significantly affect purchase decisions (Kumar, Lee, & Kim, 2009). Additionally, consumers' perceptions of product functionality and quality are acknowledged as the main drivers of purchase intention in marketing.

When faced with an array of brand options, product functional value serves to provide consumers with reasons to buy. The functional experience of different products can differentiate a specific product from other brands through the consumer experience.

As previously mentioned, functional value can be divided into quality and price. Perceived quality reflects consumers' impressions of product quality and function, primarily defined as consumers' overall evaluation of products based on internal performance (e.g., product performance and durability) and external characteristics (e.g., brand names). This implies that quality perception depends on various factors, such as when and where the product or service is purchased or used. Consumers' implicit perception of a brand's quality supersedes its price (Dodds, Monroe, & Grewal, 1991) when making a purchasing decision. However, it is evident that in reality, many products have prices that do not correspond to their function and quality. For instance, in the luxury industry, the price of products is seldom determined by the product's functional value. In such cases, to better study pricing and consumer behaviour, researchers should place greater emphasis on the product's social and emotional value.

Product Social Value

In consumer behaviour research, some scholars have observed a shift among new generation consumer groups, where the influence of material products' practical value on purchasing behaviour is diminishing, while the impact of products that confer status and prestige is increasing (Goldsmith, Flynn, & Kim, 2010). This new generation of consumers is more inclined to consider the opinions of others within their social circles, leading to consumption behaviour changes, such as luxury industry consumer behaviour driven by status-seeking (Lea, Webley, & Walker, 1995). Rapid economic development and higher per capita disposable income have made high-end products and services accessible to a broader population, no longer restricted to the upper class (Kastanakis & Balabanis, 2012). Consequently, the value of luxury items is evolving, transitioning from mere symbols of wealth to markers of social status (Trigg, 2001). This highlights the growing importance of the social value dimension in product value perception, particularly among younger consumers.

The social comparison theory can potentially explain the origins of this value perception (Lea et al., 1995), as individuals compare themselves to others to demonstrate their belonging to a group that is current and knowledgeable about the latest trends. Leibenstein introduced the "bandwagon effect" to describe the increase in demand resulting from a higher proportion of people choosing to buy a product (Leibenstein, 1950), which can also shed light on the source of product social value perception. Moreover, when a product can elevate a consumer's social status and recognition, they are often willing to pay higher prices for it. For status-seeking consumers, price serves as a tool to distinguish themselves from others (Dubois & Duquesne, 1993).

Leibenstein also coined the term "snob effect" to elucidate the behaviour of individuals who make purchases based on high prices or uniqueness to differentiate themselves from others in a social group (Leibenstein, 1950). Such consumers are prepared to pay more to display their wealth and social status. Consequently, products that signify status and wealth are perceived as having higher value among this group, making them willing to pay the corresponding amount for the purchase, even if the product's function and quality do not justify its price (Amaldoss & Jain, 2005).

In summary, the literature reveals that the social value dimension of products is becoming increasingly significant, especially among younger consumers, due to factors such as social comparison theory and the bandwagon and snob effects. These insights can help researchers and marketers better understand the factors influencing consumer behaviour and tailor their strategies to cater to the evolving consumption preferences of the new generation.

Product Emotional Value

The concept of emotional value pertains to the emotional states experienced during the consumption of products or services, which can encompass positive emotions such as enjoyment and happiness or negative emotions like fear, anxiety, and pain. In numerous cases, emotional value serves as a mediator in value perception due to the significance of emotions in social behaviour. Research on customer perceived value demonstrates that, in comparison to other value dimensions, emotional value constitutes a crucial driving force for attaining favorable theoretical outcomes. Additionally, studies on customer perceived value reveal that certain value dimensions precede others. For instance, in an analysis of green product purchasing behaviour, researchers discovered that although a product's functional value is a factor consumers must consider during the purchasing process, effective predictions of consumer behaviour cannot be made based solely on the product's functional attributes.

More accurate purchase predictions (Gonçalves, Lourenço, & Silva, 2016) emerge when both consumers' emotional factors and product attributes are taken into account. This research not only highlights the critical role of consumers' personal value judgments and products' emotional value in the purchasing process but also lends robust support for devising sales strategies tailored to different consumer types. Shamila and Muhammad's research suggests that while consumers' emotional value perception may not directly influence purchasing decisions, it does impact other value perception dimensions (Khan & Mohsin, 2017). They contend that emotional value, as a mediator, can significantly affect the influence of a product's functional, social, and societal value.

Consequently, emotional value, as a vital dimension of value perception, is influenced by various factors. On one hand, consumers' own values and emotional attitudes determine their judgments of a product's emotional value during the consumption process. On the other hand, the consumer's social environment also affects emotional value. For example, consumers in China and the United States will perceive different emotional values for Huawei brand products due to their distinct social environments. Therefore, a product's emotional value not only differs among individual consumers and social evaluation contexts, but also fluctuates across space and time. Thus, when examining emotional value in consumption, it is essential to consider the consumer group's personality and the product style evaluation information within the current social environment. This approach enables a more accurate and comprehensive understanding of the significance of consumers' perceived emotional value and its mediating effect.

2.4 Influence of Brands on Consumer behaviour

Brand equity constitutes the central notion in the realm of marketing. Pioneering contributions to this domain were made by Aaker and Keller in 1991 and 1993, respectively (D. A. Aaker, 1991; Keller, 1993). Aaker conceptualised brand equity from a cognitive psychology standpoint, defining it as an amalgamation of assets and liabilities associated with the brand, as well as its name and symbols

(D. A. Aaker, 1991). These assets and liabilities possess the capacity to augment or diminish the supplementary value of the products or services offered by the branded organization to a certain degree.

Subsequently, in 1993, Keller posited an alternative perspective, delineating brand equity as the variegated responses of consumers to brand marketing, as perceived through the consumer lens (Keller, 1993). From this vantage point, scholars investigate brand equity in relation to brand recognition, as well as the brand's potency, advantages, and distinctiveness within the consumer consciousness. The majority of research endeavors employ consumer-centric metrics of brand equity, comprising three primary constructs: brand reputation, brand awareness, and brand loyalty. These disparate components exert influence on consumer behaviour and responses, with the ensuing sections elucidating the tripartite constituents of brand equity and their respective impacts on consumer behaviour.

2.4.1 Brand Reputation

Brand reputation can be characterised as the credibility of product information encompassed under a brand's umbrella, as defined by Erdem (Erdem & Swait, 1998). Companies owning such brands utilise a variety of marketing strategies and methods to showcase the superior quality of their products. These methods may include setting higher prices, distributing products through upscale sales channels, and offering extended warranty periods. While these activities might not always be viable in intricate market conditions, a brand's distinctiveness is rooted in the company's array of marketing strategies and initiatives (Klein & Leffler, 1981). In a study conducted by Herbig and Milewicz (1995), it was highlighted that a brand's present and future reputation is influenced by past marketing endeavors (Herbig & Milewicz, 1995). Consequently, a brand's credibility, perceived professionalism, and appeal are the cumulative results of prior and ongoing marketing investments.

In general, reputation encompasses two primary dimensions: credibility and expertise. A credible brand is perceived by consumers as being willing and capable of fulfilling its brand promise. Credibility implies a brand's commitment to delivering on its promises, while expertise signifies its proficiency in doing so (Erdem & Swait, 1998). In practice, brands can bolster their products' latent competitiveness through advertising, product design, and other measures. However, these investments incur costs that must be recuperated during subsequent sales. Consequently, if a product's information is false and discovered, its long-term sales will be adversely impacted, and the brand will fail to recoup its investment. Numerous marketing and investment efforts can ensure, to a certain degree, that a brand's messaging is accurate and reliable, thus encouraging consumers to trust this information. As a result, the more precise and comprehensive a brand's product positioning, the lower the likelihood of consumer deception, enabling consumers to gather minimal information to decide on a purchase (Srinivasan & Ratchford, 1991; Shugan, 1980).

Wernerfelt's research posits that stronger credibility signals influence consumers' expectations and perceptions of product quality, leading them to believe that credible products surpass untrustworthy ones in quality (Wernerfelt, 1988). More credible brands enhance consumers' quality perceptions of their products (D. A. Aaker, 2009), as various signals emitted by the brand may affect consumers' evaluation process of product quality (C. S. Park & Srinivasan, 1994). Thus, differing levels of brand reputation may result in varying consumer perceptions, even for products of identical objective quality. This elevation process is not exclusive to high-end products and brands; as long as mid-range and low-end products maintain authentic and credible marketing and product positioning, consumer quality perception will also improve.

Another consumer behaviour potentially influenced by brand reputation is consumers' willingness to pay or price sensitivity. In a complex market environment, numerous factors impact consumers' price sensitivity, with extensive research attempting to unveil underlying patterns. A 1979 study suggested that advertisement placements affect consumers' differentiated choices, subsequently reducing price sensitivity (Comanor & Wilson, 1979). Conversely, other studies have presented opposing perspectives (Nelson, 1974). As previously discussed, marketing strategies such as advertising enhance brand credibility, implying that shifts in credibility may influence consumers' sensitivity to prices.

Considerable debate exists within this research area, with some studies positing that various internal factors contribute to brand reputation's impact on price sensitivity. For instance, Tellis and Gaeth argued that as consumers' uncertainty about product quality escalates, they assign greater importance to price fluctuations (Tellis & Gaeth, 1990). This insinuates that the credibility of quality information, a critical element of brand reputation, should affect consumers' price sensitivity. More precisely, if consumers exhibit sensitivity to uncertainty regarding quality attributes, a decrease in uncertainty could diminish price sensitivity. In contrast, if consumers demonstrate insensitivity to uncertainty about brand attributes, uncertainty may heighten price sensitivity. Furthermore, Erdem et al. generalised this finding, proposing that uncertainty concerning any product attribute associated with brand reputation could affect consumer price sensitivity (Erdem, Swait, & Louviere, 2002).In summary, the reasons why brand reputation can affect consumers' price sensitivity may include:

- Brand reputation correlates with consumers' risk perception, and an increase in credibility may reduce perceived risk, subsequently influencing consumers' price sensitivity. According to Kahneman and Tversky's 1979 risk aversion theory, amid high product information uncertainty, consumers aim to minimize potential losses during purchases (Kahneman & Tversky, 2013). As consumers may derive less value from the transaction than the price they pay, they exhibit increased price sensitivity (Tellis & Gaeth, 1990). Therefore, by decreasing the uncertainty of product-related attributes, brand reputation enhancement can lower consumers' price sensitivity.

- As brand reputation grows, the cost for consumers to acquire information decreases, and the reduction in consumers' search and processing costs leads to diminished price sensitivity (Erdem et al., 2002). In other words, the cost of gathering and processing data also constitutes a portion of the product price during consumers' purchase processes. If an improved product reputation reduces information processing costs, consumers can achieve higher utility at the same price level. Lynch and Ariely's study on online wine purchase price sensitivity supports this notion. They discovered that when the cost of seeking information about wine declines, consumers' purchase price sensitivity also decreases (Lynch Jr & Ariely, 2000). Companies can reduce consumers' search costs for additional product information by building brand reputation. For instance, the "KFC" brand name conveys information about food type, taste, and service quality, thereby evoking positive associations.

- Reputation may elevate consumers' product expectations and psychological perception of quality, which are essential factors in reducing price sensitivity. In numerous research cases, consumers exhibit higher psychological perceptions of specific brands, ultimately resulting in a premium during transactions (D. A. Aaker, 2009). However, this does not necessarily imply that heightened expectations and quality perceptions directly lead to lower price sensitivity for the brand's products. Research by Krishnamurthi et al. demonstrated that perceived quality's effect on price sensitivity is not uniform across different quality brands. Consumers of high-quality brands exhibit relatively lower price sensitivity than those of low-quality brands (Krishnamurthi, Mazumdar, & Raj, 1992).

2.4.2 Brand Awareness

In the consumer behaviour pattern, the subconscious mind plays a crucial role in brand selection. Brand popularity serves as a significant influence on consumers' judgment during their subconscious choices. Consequently, some scholars argue that brand awareness is the most critical core element of brand equity (Azad, Al Muzahid, & Kamal, 2013). Building a strong brand necessitates increased brand awareness (Buil, De Chernatony, & Martínez, 2013). In a complex market environment, establishing a strong brand and differentiating it from competitors is essential for influencing consumers' brand choices (W. Wang & Li, 2012). This brand strength is vital for successfully outperforming competing products in fierce brand competition (Jakeli & Tchumburidze, 2012).

Since brand popularity affects brand strength comparisons in consumers' minds, more well-known brands have higher chances of standing out in consumers' brand selection processes (Balaji, 2011). This notion is also evident in early studies on the impact of brands on consumer behaviour. Aaker's 1991 study highlighted that brand awareness provides customers with sufficient reasons to choose a brand's products (D. A. Aaker, 2009).

Brand recognition encompasses several levels, starting with brand recognition and culminating in the most critical stage of brand recall (Keller, 1993). Consequently, brand awareness is defined as consumers' ability to recognize or recall a product's brand under different circumstances. High brand awareness ensures a constant brand presence in the market. Keller proposed that brand awareness breadth represents the range of purchase motivations that may emerge from the brand name (Keller & Aaker, 1998). Several factors typically contribute to a brand achieving high brand awareness: continuous advertising campaigns, and product presence and distribution that impact diverse groups (Foroudi, Melewar, & Gupta, 2014; MASHUR et al., 2019).

A well-managed brand generates customer satisfaction and value attributes (Macdonald & Sharp, 2000). To measure a brand's awareness, researchers have introduced several well-known indicators (H. Ha & Perks, 2005), such as the satisfaction and pride experienced by consumers (D. Aaker, 2010), the ease of recognition by consumers (Balmer, 2001), and the influence on consumers' final decisions (MASHUR et al., 2019). Previous research demonstrates that brand awareness affects consumers' product decisions. The higher the brand awareness, the more likely consumers will opt for that brand when purchasing (Dabbous & Barakat, 2020). Dabbous and Barakat's study on younger generation consumption behaviour revealed that brand awareness has become a vital variable impacting consumers' purchase choices (Dabbous & Barakat, 2020). Additionally, brand awareness is among the key factors influencing consumers' purchase interest. For instance, some brands aim to control and influence consumers' interest, positioning themselves as one of the alternative brands consumers choose for future purchases (Curina, Francioni, Hegner, & Cioppi, 2020).

In summary, the current research landscape illustrates that brand awareness plays a vital role in consumer behaviour, influencing purchase decisions and interests across various demographics. Studies show the importance of building and maintaining strong brand awareness in a competitive market to differentiate from competitors and ensure long-term success. These research findings highlight the need for ongoing investigation and understanding of brand awareness' role in consumer behaviour and decision-making.

2.4.3 Brand Loyalty

The study of brand loyalty has emerged as a prominent topic within the fields of business administration and marketing research. While various research literature explores its influence, brand loyalty generally refers to the tendency of consumers to favor a specific brand, resulting in consistent purchasing behaviour over time (Jacoby & Kyner, 1973). Despite the absence of a universally accepted definition, most researchers and practitioners concur that brand loyalty significantly impacts a firm's sales and profit levels.

A vast array of marketing literature delves into brand loyalty, examining its nature, significance, and consequences. Given the diversity of perspectives on this subject, brand loyalty manifests in numerous ways in the literature. Fundamentally, it pertains to consumers' propensity to prefer a certain brand, leading to consistent purchasing behaviour over time. Although a broadly agreed-upon definition remains intangible, it is widely acknowledged that brand loyalty affects a company's sales and profit levels (Bennett & Rundel-Thiele, 2005; Gounaris & Stathakopoulos, 2004).

Enhancing brand loyalty is considered a virtuous cycle for a company's revenue. Loyal customers provide a stable future income stream without incurring additional customer acquisition costs. Consequently, companies can allocate the reduced costs towards organizational and product improvements, ultimately elevating customer satisfaction through superior products and services. This process, in turn, further stimulates consumer brand loyalty (Datta, 2003; Melton, 2004).

The current research landscape underscores the importance of brand loyalty in business administration and marketing research. The various studies highlight brand loyalty's role in influencing sales, profits, and customer satisfaction. Despite the absence of a universally accepted definition, the consensus among researchers and practitioners emphasizes the need for ongoing exploration and understanding of brand loyalty's impact on consumer behaviour and business performance. Comparing the different approaches in the literature can help illuminate how brand loyalty manifests and evolves, providing valuable insights for businesses seeking to optimise their strategies and foster long-term customer

2.5 Research Questions and Hypotheses

2.5.1 Platform Choice Problem

Through the literature review presented above, we can identify several key factors influencing second-hand transactions and product selection, which provide insights for investigating the three questions posed in Chapter One. Firstly, regarding platform selection, previous research indicates that consumers' economic status plays a significant role in their choice of second-hand platforms. Secondly, the brand of the purchased product has a notable impact on consumers' willingness to pay. Lastly, consumers' perceived value of the product is another essential factor. Other variables, such as age and gender, have also been mentioned in prior studies. However, previous research has primarily focused on analysing consumer behaviour on individual second-hand platforms. Our study aims to examine consumers' decision-making when faced with two platforms by analysing the shopping behaviour of the same group of people across both platforms. In Chapter 3 of this article, we will investigate the platform choice issue between first-hand online platform Taobao and second-hand online platform Xianyu. And we proposing three potential factors that may influence consumers' final platform selection decisions, which are as follows:

1) **The purchasing power of the consumers** represents the economic level of buyers of second-hand goods.

2) **The brand score of the product** consumers wants to buy. The product with

a higher brand score represents a more luxurious brand. Examples of cars are Mercedes, with a higher brand score, and Toyota, with a lower brand score.

3) **The type of product**, whether it leans more towards functional value or emotional value. Goods with higher emotional value indicate that consumers pay more attention to the show-off function it brings when using the product. Consumers are more concerned about their functionality when using products with higher functional value. For example, consumers purchasing electronics such as mobile phones may be more concerned with the functional value of the product, while those purchasing fashion items such as skirts may place greater emphasis on the emotional and conspicuous value of the product.

With reference to the questions above, three hypothesis have been formulated as follows:

- **Hypothesis 1**: The consumption level has no impact on the probability of the Xianyu second-hand platform selection.
- **Hypothesis 2**: The product's brand score has no impact the probability of the Xianyu second-hand platform selection.
- **Hypothesis 3**: The emotional value (functional value) of the product has no impact on the probability of the Xianyu second-hand platform selection.

2.5.2 Influencing Factors of Second-Hand Product Purchasing Intention

In the previous literature summary, we mentioned that information asymmetry in second-hand transactions can lead to a decline in purchasing intentions. Additionally, perceived risk is a crucial component of consumers' perception of product value. Consequently, the second research question regarding consumers' willingness to buy primarily targets the influence of perceived risk in an online environment. It is important to note that in the context of online second-hand transactions, consumers' risk perception is not solely determined by the seller's characteristics; buyers' risk tolerance and risk perception levels may also be related to their experience and the degree of similarity between their own and the seller's characteristics.

In Chapter 4 of this article, we attempt to find answers to this issue. We employ data analysis and logistic regression modeling to validate several factors that may influence consumers' willingness to purchase second-hand goods. These factors include user information (encompassing both buyers and sellers) such as **Xianyu usage experience**, **age**, **gender**, **geographic location**, and **historical review**, as well as information related to the **title** and **description** of online second-hand product posts. Then we give four hypothesis:

- **Hypothesis 4**: The buyer's and seller's historical experience of using the Xianyu App will not impact the further purchase intention
- **Hypothesis 5**: The seller's historical evaluation information will not affect the buyer's purchase intention
- **Hypothesis 6**: Gender and geographic match of seller and buyer do not affect purchase intent of the buyer
- **Hypothesis 7**: The length of the title and description of the product post does not affect the buyer's willingness to purchase

2.5.3 Chat Strategies in Online Second-Hand Transactions

Prior literature reveals that second-hand transactions have a strong social aspect, with the success of transactions likely related to communication and interaction between buyers and sellers. Previous research has not specifically investigated the impact of communication skills between buyers and sellers on the final transaction outcomes in an online second-hand trading environment. In Chapter 5 of this article, we attempt to find out the influencing of chat strategies in online second-hand transactions. Firstly, we employ machine learning-based natural language processing techniques to extract information on the **emotional states**, **conversation motivations**, and **bargaining strategies** of both buyers and sellers within their chat data. We then utilise visualisation techniques and statistical testing methods to investigate the influence of different factors. Finally, we establish various machine learning prediction models to forecast second-hand transaction conversion rates under different scenarios. The following two hypothesis are what we want to verify:

- **Hypothesis 8**: The Emotional state during chat has no significant effect on final transaction conversion
- **Hypothesis 9**: The motivational language and bargaining strategy during the chat had no significant impact on the final deal conversion

Chapter 3 A Statistical Approach on Consumer Online Purchasing Decision and its Influencing Factors: A Comparison between Taobao and Xianyu

3.1 Research Question Description

Alibaba Group is one of the largest e-commerce companies in China. Taobao and Xianyu are two popular online shopping platforms under the Alibaba Group. Among them, on the Taobao platform, consumers can buy various brand-new products in online stores, mainly a C2B first-hand commodity trading platform. The products sold on the Xianyu platform are mostly second-hand goods. Users can buy and sell second-hand goods on the Xianyu platform, mainly a B2B second-hand trading platform. Assuming that a consumer is both a Taobao user and a Xianyu user. Then, when they choose to buy a product, they will face a choice: Xianyu or Taobao. On the Taobao platform, consumers can buy brand-new products, and the stores they buy the products have sufficient credit. At the same time, the Taobao platform will provide after-sell service to ensure that the purchased products meet consumers' expectations. On the Xianyu platform, consumers can buy cheaper products, but the B2B transaction model determines this will be risky. Consumers may buy fakes or products that do not meet expectations. Therefore, the final decision to purchase the product on which platform is the result of considering many impacts, like commodity prices, consumers' economic situation, transaction risk levels, etc.

With the development of the sharing economy, more and more consumers have become active users of second-hand trading platforms. As a result, the number of consumers should decide between primary trading platforms such as Taobao and second-hand trading platforms such as Xianyu when purchasing goods. At the same time, e-commerce platforms are also faced with the problem of choice in operation:

whether to push second-hand commodity information to consumers or first-hand commodity information to consumers and which one can attract consumers' interest more. To understand these questions, we need to examine which factors significantly influence consumers' choice of platforms when purchasing goods. The answer to this problem is not only an interesting theoretical discovery. However, it can also help companies conduct more accurate advertising in the application process so that consumers can more easily purchase satisfactory products. In Section 3.2, we present the data used for the analysis and define the relevant variables to be studied. In Section 3.3, we mainly analyse the influence of consumers' characteristics on platform choice. Then in Section 3.4, we mainly analyse the influence of the characteristics of the product which consumers want to purchase on the decision of their platform choice. Finally, in Section 3.5, we give a summary of the discussion in this chapter.

3.2 Data and Variables Introduction

3.2.1 Data collection

As described in the previous section, we want to explore how a consumer, who is both activated in Taobao and Xianyu platforms, makes decisions when faced with a platform choices problem. Therefore, we need to find the data of users that fit the above assumptions. Since both Taobao and Xianyu are affiliated with Alibaba Group, users on these two platforms share the same account. In this situation, we have the opportunity to obtain data on the consumption behavior of users on both platforms. By comparing the different behavioural characteristics of these users when they purchase goods on the two platforms, we can get what factors affect consumers' preferences in choosing different platforms.

The data used in our research comes from accurate transaction records on the Xianyu and Taobao platforms. The first step in data collection is to select a suitable group of consumers. As the research object, we screen out consumers who have purchased more than or equal to 1 product in the Xianyu platform in the past 180 days, ensuring that these users are active users of the Xianyu app. At the same time, due to the enormous size of the Taobao platform and its sufficient popularity in China, we believe that users who participate in Xianyu shopping must be familiar with the Taobao platform. Through the above two points, we think that the users involved in the data satisfy our previous assumption that they are active users in both first-hand and second-hand platforms. Consumers' personal information includes age, gender, consumption level, purchase volume on the Xianyu platform in the past 180 days, and sells volume on the Xianyu platform in the past 180 days.

After randomly selecting a set of consumers that meet our standards, we searched all the purchase records of these consumers on the Xianyu and Taobao platforms within a period of time. The data records the category and brand information of the goods consumers purchase in each transaction. Due to the large gap between the transaction volume of many categories of commodities on the Xianyu second-hand platform and the Taobao platform, we selected six commodities for which the gap is manageable for research. These categories of commodities included digital accessories, audio-visual appliances, cell phone, camera, popular clothing and bag. We can see that these commodities can be divided into two categories: digital products (digital accessories, audio-visual appliances, cell phone, camera) and apparel products (clothing and bag). The flow of data collection is shown in Figure 3-1 below, the data-set used for modeling and analysis is the final **transaction record dataset**.

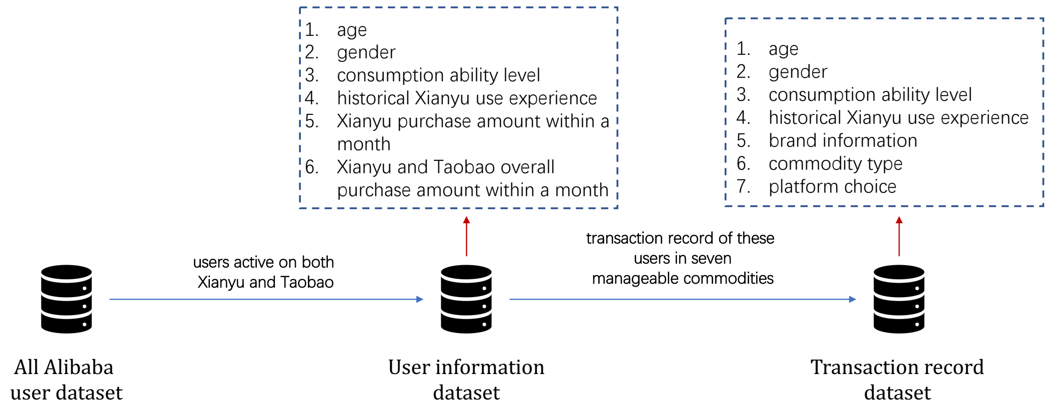


Figure 3-1 Data Collection Process of Platform Selection Analysis

3.2.2 *Variable description*

This chapter of the research mainly wants to determine what factors affect consumers' choice of platform. We will analyse the impact of platform selection from two aspects of user characteristics and product characteristics. In the analysis part of user characteristics, we use subscript i to denote different users. And the impact indicator we focused is the proportion of users choosing Xianyu platform when shopping XP_i within a certain period of time, which is calculated as following

$$XP_i = \frac{\text{The amount of purchase by user } i \text{ on Xianyu in the period}}{\text{The amount of purchase by user } i \text{ on both Xianyu and Taobao in the period}} \tag{3.1}$$

In the analysis part of commodity characteristics, we use subscript ij to denote the relevant events of consumer i in transaction j. Our **dependent variable** is the platform choice of consumers to finally purchase the items, which is a binary variable PC_{ij} with two value: *Xianyu* or *Taobao*. There are four important factors focused in our analysis: consumers' consumption level C_i, the experience of using the Xianyu platform P_i, the item category they purchased IC_{ij}, and the brand score of the item IB_{ij}. We want to verify whether and how they affect consumers' platform choices.

Consumption Level

From previous research results, we know that economic motivation is vital for consumers to choose second-hand goods (Guiot & Roux, 2010; Williams & Paddock, 2003; Gregson & Crewe, 1997; Stone et al., 1996). Except for some commodities that are no longer on sell in the first-hand market (such as old iPhones), the properties of commodities on first-hand platforms are better than those on secondary platforms. Consumers choose second-hand platforms for consumption, usually because of economic considerations.

Therefore, we collected the consumption level of consumers C_i as an independent variable. This is a numerical variable, with integers 1 to 5 representing the consumption level from small to large. The consumption level score value we use here is based on Alibaba's e-commerce transaction data and Ant Financial's (an internet financial services company under the Alibaba Group) internet financial data. The score is obtained by comprehensive processing and evaluation of massive information data through cloud computing, machine learning, and other technologies.

Experience of Using the Xianyu Platform

Online second-hand trading is a risky trading behavior. Due to the information asymmetry of second-hand transactions and the uncertainties in the online trading environment, buyers and sellers may face various risks in trading, such as buying fake or unsatisfactory goods(S. Ha & Stoel, 2009; E. J. Park et al., 2012). As a result, an inexperienced consumer may be concerned that his or her interest will be harmed in the process of second-hand trading online. Hence, the experience of using the Xianyu app should also be considered as the independent variable in our analysis.

In this research, We measure the consumers' experience of using the second-hand platform by the number of purchases orders on the Xianyu platform over the past 180 days denote as PS_{ij}. We can see from the data that some users have had very high purchase orders in the past 180 days. These users may be professional buyers on the Xianyu platform, and their purchasing motives and behavior patterns may not be the same as regular users. Therefore, we will filter out these data record, which the buyer with $PS_i > 200$, in the subsequent data-processing process. We give a define of the variable experience of using the Xianyu platform P_i by formula 3.2.

$$P_i = \begin{cases} k & \text{when } (k-1)\times 10 < PS_i \leq k \times 10 \text{ for } k \in [1,5] \\ 6 & \text{when } 50 < PS_i \leq 200 \end{cases} \tag{3.2}$$

Item Category

In the previous introduction about data collection, we mentioned that seven specific products (including digital accessories, audio-visual appliances, cell phones, cameras, popular clothing and bags) were selected as the research targets to reduce the sales gap between Xianyu and Taobao as much as possible. For apparel products like clothing and bags, consumers more concern about the appearance of these products while purchasing. Consumers pay more attention to the emotional value brought by the show-off attributes of these products. Hence, we alao call these apparel products as *emotional products*. At the same time, for digital products such as mobile phones and cameras, consumers tend to pay more attention to the functional value of these products. We also call these digital products as *functional products*. Hence, we have

$$IC_{ij} = \begin{cases} \text{apparel products} & \text{when user } i \text{ buy apparel products in transaction } j \\ \text{digital products} & \text{when user } i \text{ buy digital products in transaction } j \end{cases} \tag{3.3}$$

The functional and emotional values determine a product's perceived value together (Khan & Mohsin, 2017; Gonçalves et al., 2016; H.-P. Lu & Hsiao, 2010; Hsiao, 2013). In addition, previous research has found that the perceived value of a product is an essential factor affecting consumer purchasing behavior (Z. Li et al., 2013; Pham et al., 2018; Silva et al., 2018). Therefore, when faced with functional and emotional products, whether consumers' shopping platform choices are different is an interesting question that we want to discuss.

Brand Score

Many studies reveal the influence of brands on consumer behavior. The reputation and level of different brands will bring different value perceptions to consumers (Srinivasan & Ratchford, 1991; D. A. Aaker, 2009; C. H. C. Hsu, Oh, & Assaf, 2012; Huang & Cai, 2015). Most of these studies focus on the first-hand commodity market, and there are few studies on the impact of brands on consumer behavior in the secondary market. Therefore, we collected brand information on the items involved in each transaction, hoping to explore their impact on consumer behavior in the online second-hand market. However, there are too many types of brands involved in the data, and it is difficult to use them directly. We simplified the brand information based on the scoring results of Alibaba's consumer market experts on these brands. Each product is given a brand score ranging from 1 to 6, indicating that the products are from different levels of brands.

$$A_i = \begin{cases} 1 & \text{when } 0 < \text{buyer's age} < 18 \\ 2 & \text{when } 18 \leq \text{buyer's age} < 25 \\ 3 & \text{when } 25 \leq \text{buyer's age} < 35 \\ 4 & \text{when } 35 \leq \text{buyer's age} < 45 \\ 5 & \text{when } 45 \leq \text{buyer's age} \end{cases} \tag{3.4}$$

In addition to the variables discussed above, the age A_i and gender G_i of the consumer of a piece of data is also recorded in our data. Here we do not apply the exact age value but use different age groups in the following model for analysis. This approach is based on Alibaba's rule in the age structure division of the e-commerce users. The specific division method is as 3.4.

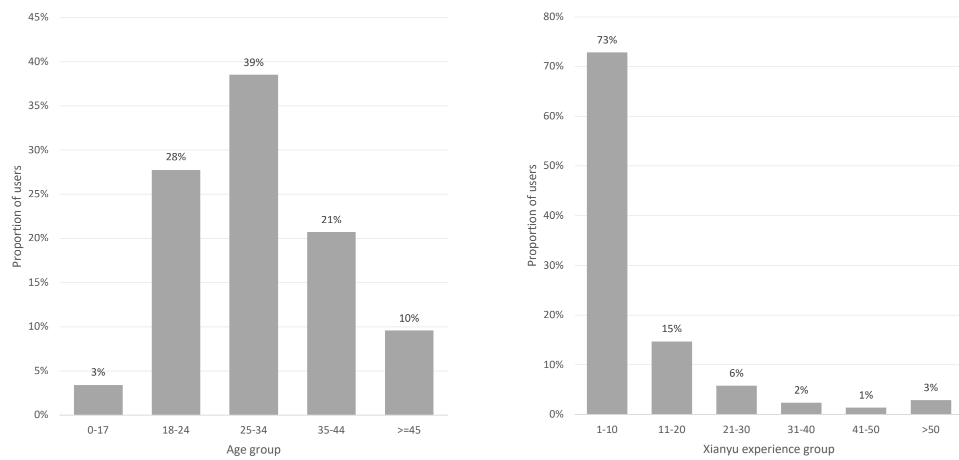
3.3 User Characteristics Analysis

3.3.1 Descriptive Statistics of Variables

In this section, we analyse the characteristics of users who are active on both platforms, these analysis based on the data without introducing specific transaction information and product information. This means that the data used in this part of analysis is the **user information dataset** in Figure 3-1. First, we give the descriptive statistics of the variables we concerned in this section, include the age (raw data, not processed by 3.4), gender, Xianyu experience (raw data, not processed by 3.2) and consumption level. We can see from Table 3-1 that, for both platform active users, 47.43% of them are female, the proportion of male is a little bit higher. The average age of these users is 30.74, of which the average age of male users is 31.63 years old, and the average age of female users is 29.76 years old. The distribution of different age group are shown in Figure 3-2 (a), users generally belong to the younger generation, and female users are relatively younger than male. The average consumption level of users buy these items Xianyu platform is 2.99. In the past 180 days, these users purchased an average of 9.52 items on the Xianyu platform and the distribution of different Xianyu purchase experience group are shown in Figure 3-2 (b).

Table 3-1 Descriptive Statistics Analysis of User Characteristics

Variable	Obs	Mean	Std.Dev	Median
Female percent	9812	47.43%	-	-
Age	9812	30.74	9.83	29.0
Consumption level	9812	2.99	1.31	3.0
Xianyu experience	9812	9.52	1.58	4.0



(a) Age distribution (b) Xianyu experience distribution

Figure 3-2 The Distribution of Different Age and Xianyu Experience of Users

3.3.2 Quantitative Analysis and Hypothesis Testing

Next, we analysis the four variables mentioned above and the significance test of their impact on the platforms choice. The primary method and tool used in this section is the `ggstatsplot` package in R (Patil, 2021). This toolkit provides professional data visualisation methods and simultaneously shows the results of the significance test in the figure.

Gender

First, we compare the difference in the average proportion of Xianyu purchase XP_i in different genders over a period of time, the Hypothesis is shown in 3.5.

$$H_0 : \text{The choice of platform independent from customer gender} \tag{3.5}$$

we can get the mean value of XP_i in the group of male is 0.39 and the mean value of XP_i in the group of female is 0.26. The p-value of the T test less than 0.001 which suggest that the Xianyu purchase rate is significantly different in male group and female group. We can reject the Hypothesis 3.5, gender will significantly impact the platform choice decision of users, male will more likely to choose the Xianyu platform for shopping.

Age

Then, we compare the Xianyu purchase rate in different age group, the Hypothesis is 3.6.

$$H_0 : \text{Users' age will not affect the platform choice while purchase} \tag{3.6}$$

we can use the `ggbetweenstats` command to compare the average of XP_i in different age group. We can see from Figure 3-3 that the proportion of Xianyu users in different age groups shows a U-shape trend of first decreasing and then increasing.

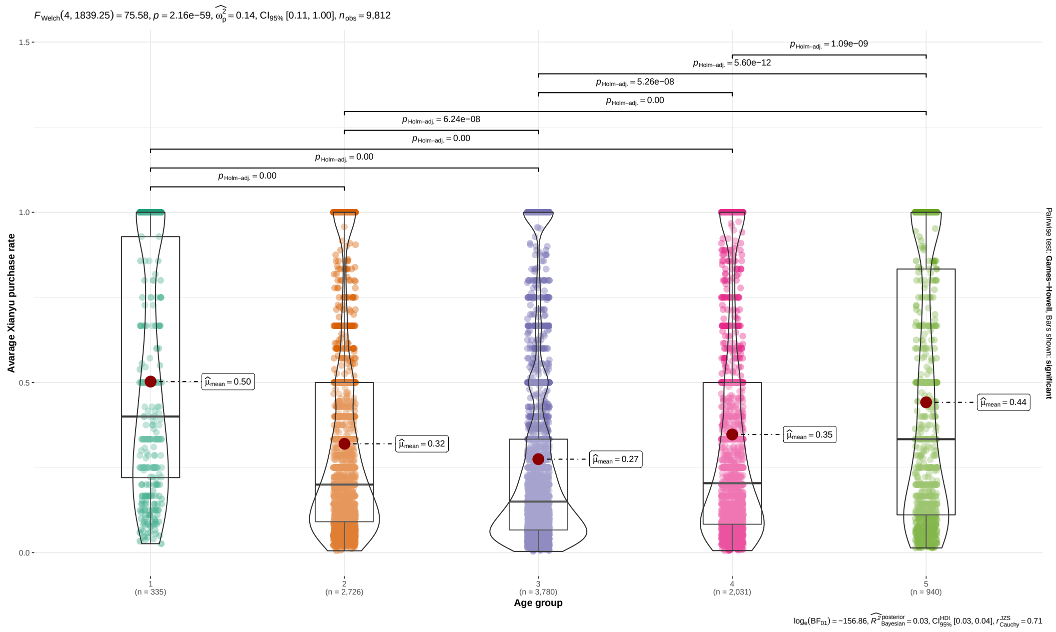


Figure 3-3 Average Xianyu Purchase Rate PX_i in Different Age Group

The descending stage is from under 18 to 24 years old, and the ascending stage is from 24 years old to over 45. Comparing Figure 3-2 (a) and Figure 3-3, it can be seen that the changing trends of the two are completely opposite. The Xianyu platform is more popular among the minority of younger and older groups and the least popular among the majority of 25-34 age group. The p-value of *Fisher* test less than 0.001, it can be concluded that the Xianyu choice rate change with the age significantly. Hence, we can reject the hypothesis 3.6.

Experience of Using Xianyu App

Then, we also do a simple test about the impact of users' experience of using Xianyu App on the future Xianyu purchase rate, the Hypothesis is

$$H_0 : \text{Users' historical Xianyu experience independent from future platform choice} \tag{3.7}$$

we also use the `ggbetweenstats` command to compare the average of XP_i in different historical purchase group P_i. The Xianyu purchase rate change within the past 180 days purchase group is shown in Figure 3-4.

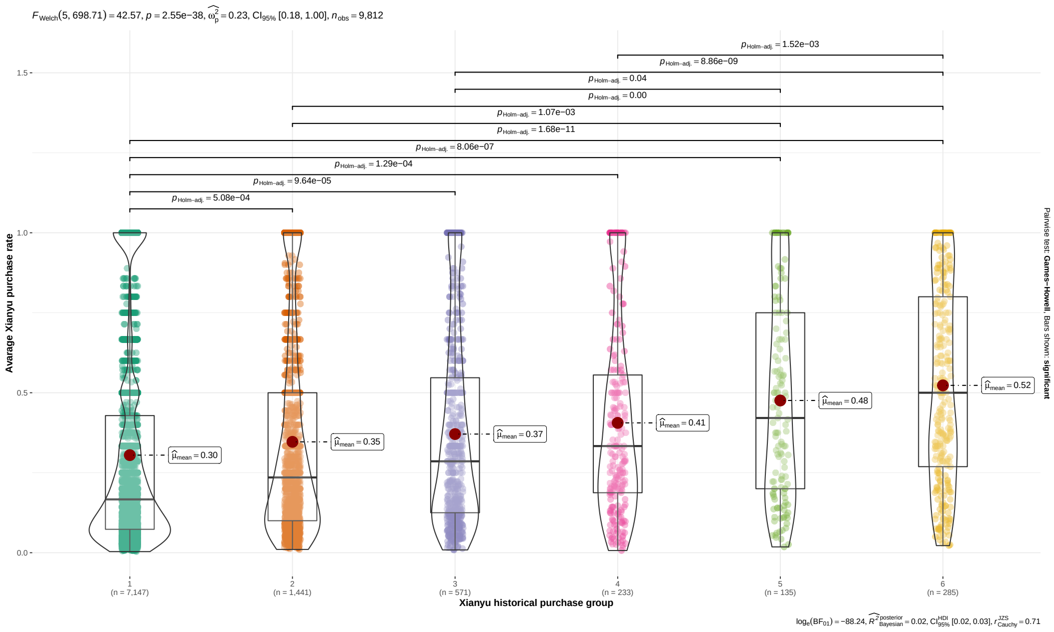


Figure 3-4 Average Purchase Rate PX_i in Different Historical Purchase Group

We can find that with the increase in consumer purchases on the Xianyu platform in the past 180 days, the Xianyu purchase rate gradually increased. The *p*-value of *Fisher* test less than 0.001, which suggest that the Xianyu choice rate change with the historical Xianyu purchase experience significantly. And we can strongly rejected the null hypothesis that the choice of platform independent from past 180 days Xianyu purchase. As we have introduced before, online second-hand trading is a risky form of trading. Users with rich historical experience are more likely to have stronger anti-risk capabilities and are more likely to choose this trading method.

Consumption Ability Level

A more detailed analysis about the impact of consumption levels on platform choice is discussed in the next Section 3.4. Because the impact of consumption level is affected by the product characteristics such as product type IC_{ij} and product brand score IB_{ij}. In this part, we give a simply Table 3-2 describe the relationship between consumption levels and platform choice. We can see that with the growth of consumer consumption level, the rate of choosing the Xianyu platform to buy second-hand goods gradually decreases.

Table 3-2 Impact of Consumption Levels on Platform Choice

Consumption level	1	2	3	4	5
Average Xianyu purchase rate	59%	36%	27%	23%	24%

3.4 Regression Analysis About the Platform Choice

The two important characteristics of commodities include item brands, and item types (classified according to the functional and emotional value of the products) are the focus of our discussion in this section. Among them, the item type IC_{ij} is an important moderating variable we want to discuss. We want to explore the different impacts of other variables on consumers' platform choice decisions when faced with varying types of products. Therefore, we will use the **Transaction dataset** shown in Figure 3-1 and split the whole dataset into two sub-datasets based on the item type of *digital product* and *apparel product*. Then, we can get a digital product dataset and a apparel product dataset. The following data analysis and regression model establishment will be based on these two different datasets.

3.4.1 Descriptive Statistics

First, we denote digital product dataset as (1) and apparel product dataset as (2), then show the platform selection situation in the two datasets in Table 3-3. We can see that there are 1939 pieces of record in the digital product dataset, less than the apparel product dataset, which has 4590 pieces of record. In the dataset that records digital commodity transactions, 28.57% of the transactions occurred on the Xianyu second-hand platform. In contrast, for emotional items such as clothes and bags, only 14.1% of the transaction happened on the Xianyu platform.

Table 3-3 Descriptive Statistics of Two Datasets

	Obs	Xianyu purchase amount	Xianyu selection rate
(1)	1939	554	28.57%
(2)	4590	647	14.10%

Then we give the basic information of each variable in the two datasets in Table 3-4.

Table 3-4 Descriptive Statistics Analysis of Item Characteristics

Variable	Mean		Std.Dev		Median	
	(1)	(2)	(1)	(2)	(1)	(2)
Female percent	38.58%	80.72%	-	-	-	-
Age	31.01	30.87	9.59	8.01	30.00	30.00
Xianyu experience	13.22	14.17	21.35	21.11	5.00	6.00
Consumption level	3.37	3.73	1.23	1.13	3.00	4.00
Brand score	3.50	2.52	1.85	1.64	3.00	3.00

Since the products in the digital product dataset are mainly products more attractive to male, the proportion of female buyers is only 38.58%, while the products in the apparel product dataset are clothes and bags, and female buyers account for the vast majority. From the perspective of gender, there is a significant difference in the gender distribution in the two datasets. There is no noticeable difference in the data performance of variables such as age and Xianyu experience in the two datasets. But for the variable of product brand score, the average brand score of products in the digital product dataset is 3.5, which is greater than the average brand score of 2.52 in the apparel product dataset.

3.4.2 Model Building and Coefficient Estimation

In this part, we will build the logistic regression model to analyse the impact of the variables describes in above sections on the platform choice of consumers. The dependent variable is the platform chosen by consumers PC_{ij} in each transactions recorded in our data. The positive outcome of the logistic regression is the consumer select Xianyu platform to buy the product. And the definition of other independent variables is shown in Table 3-5 below. The relevant definitions of the variables have been introduced in detail in Section 3.2. The age group squared term AS_i is a newly introduced variable to describe the previously observed U-shaped trend with age.

Table 3-5 The Description of Variables for Regression Model

Variable Name	Variable Description	Notation
Platform Choice	The platform where the product is ultimately purchased (Xianyu:1,Taobao:0)	PC_{ij}
Age	The age group of the consumer defined by fomular 3.4	A_i
Age square	The square value of age group equals $A_i \times A_i$	AS_i
Gender	The gender of the consumer	G_i
Xianyu experience	The group of numbers of purchase orders at Xianyu in the past 180 days defined by fomular 3.2	P_i
Consumption level	From 1 to 5, the higher value indicate consumer have stronger consumption ability level	C_i
Item brand score	From 1 to 6, the higher value indicates the items are more premium brands	IB_{ij}

Before modeling, we need to do a multicollinearity test on the variables to ensure that there is no significant correlation between different variables. We used the `vif()` command of `car` package in the `R` language to do the multicollinearity test, and the results for the two datasets are shown in Table 3-6 below. We can see that the value of Variance Inflation Factor(VIF) of each variable are smaller than 2, which indicates that there is no significant collinearity between the variables.

Table 3-6 The Description of Variables

Variable Name	VIF for digital dataset	VIF for apparel dataset
Age	1.048	1.079
Gender	1.016	1.027
Xianyu experience	1.19	1.09
Consumption level	1.14	1.20
Item brand score	1.12	1.07

Then, we can write the function of the regression model in 3.8, where α_1 denote the interaction effect of consumers' consumption level and the item brand score.

$$\begin{gathered}\mathscr{L}(PC_{ij}) = \beta_0 + \beta_1 A_i + \beta_2 AS_i + \beta_3 G_i + \beta_4 P_i + \beta_5 C_i + \beta_6 IB_{ij} \\ + \alpha_1 C_i \times IB_{ij} + \varepsilon\end{gathered} \tag{3.8}$$

The coefficient of the regression model was estimated by the `glm()` function in `R` and shown in Table 3-7. We also tried the models without the interaction item α_1, but the Akaike information criterion(AIC) value of the model without the interaction item is bigger than model 3.8 in both of the two datasets (Akaike, 1974). Hence, we will use the model with the interaction item α_1 to explain the variables impact.

Table 3-7 Regression Result of Model 3.8

Digital product dataset				
Characteristic	**Coefficient**	**95%CI** [1]	***p*-value**	**OR** [2]
Intercept	-6.93	$(-8.7, -5.2)$	**< 0.001**	0.00098
Age	-0.93	$(-1.8, -0.06)$	**0.036**	0.39
Age square	0.16	$(0.03, 0.29)$	**0.019**	1.2
Gender				
Female	-	-	-	-
Male	0.99	$(0.69, 1.3)$	**< 0.001**	2.7
Xianyu experience	0.39	$(0.30, 0.49)$	**< 0.001**	1.5
Consumption level	0.51	$(0.13, 0.89)$	**0.008**	1.7
Brand score	1.6	$(1.3, 1.9)$	**< 0.001**	5.0
Consumption level× Brand score	-0.19	$(-0.26, -0.11)$	**< 0.001**	0.83

Apparel product dataset				
Characteristic	**Coefficient**	**95%CI** [1]	***p*-value**	**OR** [2]
Intercept	-1.71	$(-2.77, -0.65)$	**< 0.001**	0.18
Age	-1.4	$(-2.0, -0.78)$	**< 0.001**	0.25
Age square	0.24	$(0.14, 0.33)$	**< 0.001**	1.3
Gender				
Female	-	-	-	-
Male	-0.25	$(-0.50, 0.00)$	0.051	0.78
Xianyu experience	0.56	$(0.51, 0.62)$	**< 0.001**	1.8
Consumption level	-0.32	$(-0.52, -0.13)$	**< 0.001**	0.72
Brand score	0.78	$(0.59, 0.97)$	**< 0.001**	2.2
Consumption level× Brand score	-0.06	$(-0.11, -0.01)$	**0.014**	0.94

1. CI = Confidence Interval **2**. OR = Odds Ratio

3.4.3 Discussion of the Variable Impact

In the previous section, we built two logistic regression models on platform choice based on two datasets and estimate the coefficients of them. In this section, we will comprehensively analyse the data performance and regression results of different variables and discuss their influence, especially for the variable Item Brand score IB_{ij} and Consumption level C_i.

Intercept

In Table 3-7, we can see that the Intercept based on the digital product dataset model is $\beta_0^d = -6.93$ and the intercept based on the apparel product dataset model is $\beta_0^a = -1.71$ (superscript d denote digital products, a denote apparel products). The difference in the value of the Intercept reflects the degree of basic preference of platform choice for consumers when faced with these two types of goods. These two coefficients are significantly less than 0, indicating that even consumers who are active on both platforms are more inclined to choose the Taobao platform to buy first-hand goods when faced with platform choices. At the same time, the intercept coefficient of the digital product model is more than three times that of the apparel product model. This shows that the type of product IC_{ij} will significantly impacts platform choice. Compared with products with high functional value, such as digital products, consumers prefer to buy products with high emotional value, such as clothes and bags on second-hand platforms.

Age

In the analysis of section 3.3.2, we see that the influence of age on the choice of Xianyu platform presents a U-shaped trend, as shown in Figure 3-3. In the regression model, we test this phenomenon by introducing the age group and the square term of the age group. In digital product dataset based model, the coefficient of age related variable is

$$\beta_1^d A_i + \beta_2^d AS_i = -0.93A_i + 0.16A_i^2 \tag{3.9}$$

In apparel product dataset based model, the coefficient of age related variable is

$$\beta_1^a A_i + \beta_2^a AS_i = -1.4A_i + 0.24A_i^2 \tag{3.10}$$

Although the coefficients of the expressions 3.9 and 3.10 are not exactly the same, they are both in the form of a quadratic function with an upward opening on the age group A_i and the coefficients are all significantly different from 0 ($p < 0.05$). It gives sufficient statistical evidence to the conclusion that age increases lead to a U-shape trend of the selection probability of the Xianyu platform.

Gender

The previous T-test for user data analysis shows that men prefer to use Xianyu platform for second-hand shopping (shown in Section 3.3.2). Analysing the transactions in two different commodity datasets through regression models, we found that the impact of gender is different when facing various commodities. $\beta_3^d = 0.99$, which is significantly not equal to 0 ($p < 0.001$), shows that when purchasing digital products with high functional value, the odds of choosing the Xianyu platform for purchase for men are 2.7 times higher than for women. However $\beta_3^a = -0.25$, which is significantly not equal to 0 ($p = 0.051$), shows that when purchasing apparel products with high emotional value, the odds of choosing the Xianyu platform for purchase for men are lower than for women. The effect of gender is moderated by the type of goods, with men showing more preference for more functional goods in the Xianyu second-hand market. In contrast, women are more interested in products with higher emotional prices in the second-hand market.

Xianyu Experience

Similar to the results analysed in Section 3.3, the coefficients β_3 of consumer experience P_i using Xianyu are significantly positive in both models. More experienced Xianyu users are more likely to choose the Xianyu platform to purchase goods in the future. At the same time, $\beta_3^d = 0.39 < \beta_3^p = 0.57$ shows that the influence of experience is more significant when buying goods with high emotional value.

Consumption Ability Level

In the previous summary, we briefly touched upon the impact of consumer purchasing power on shopping preferences. As illustrated in Table 3-2, we can determine that as the level of consumer spending increases, the proportion of consumers choosing to shop on the Xianyu secondhand platform decreases. Here we give the trend of the proportion of Xianyu purchases as the consumption level of consumers changes in the digital product dataset and apparel product dataset.

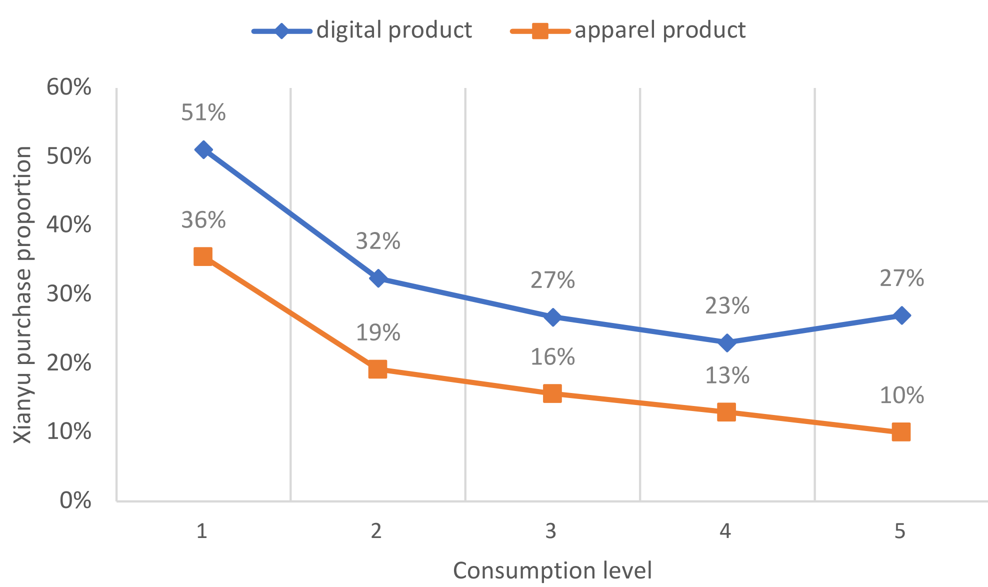
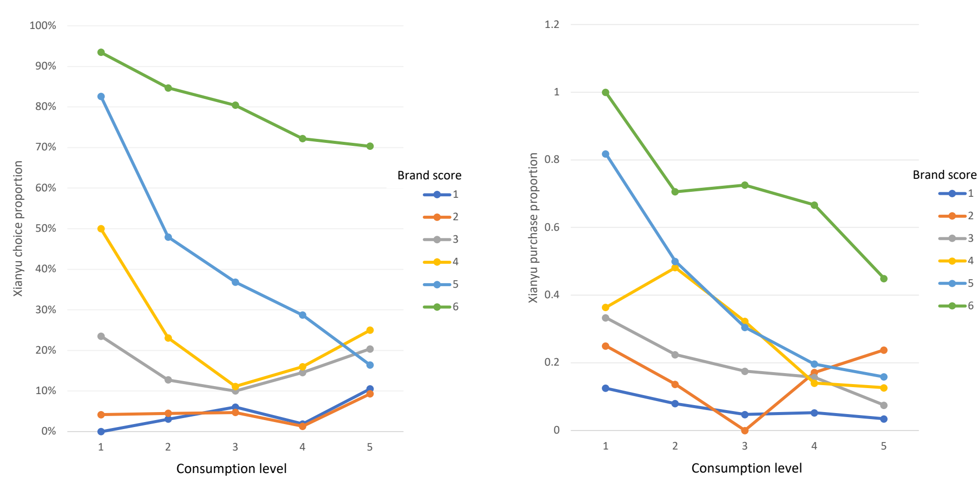


Figure 3-5 Xianyu Purchase Proportion Change with the Consumption Level

In Figure 3-5, we can see that the proportion of Xianyu purchases in both datasets decreases with the rise of consumption level, and there is no significant difference in the slope.

Then we introduce the impact of product brand scores, and we will explore the effects of consumption levels on products with different brand scores. We can see from Figure 3-6 (a) that, for digital products, when the brand score is low (when the product brand score is 1 and 2), the increase in consumption level has no significant negative effect on the Xianyu purchase proportion. The increase in consumption level significantly negatively impacts the odds of choosing the Xianyu platform only when the brand score increases to 5 and 6. But for the apparel products with high emotional value, the increase of consumer's consumption level shows a negative impact under each brand score. Simultaneously, it is noteworthy that, for two distinct product categories, augmenting brand score amplifies the magnitude of the adverse effect of consumption level on the odds of purchasing via the Xianyu platform.



(a) Digital product dataset (b) Apparel product dataset

Figure 3-6 The Impact of Consumption Level under Different Brand Score

From the results of the regression model, we can also verify the above data performance and get more rigorous evidence. For the regression model of digital product dataset, we partial derivative with respect to the consumption level C_i, we can get

$$\frac{\partial \mathscr{L}(PC_{ij})}{\partial C_i} = 0.51 - 0.19IB_{ij} \tag{3.11}$$

The values of the coefficient β_5^d and α_1^d are both significantly different from 0 ($p < 0.05$), indicating that the influence of consumption level and the interaction term are both statistically significant. Equation 3.11 indicates that when the brand score of the product is less than or equal to 2, the impact of consumption level on Xianyu's choice is positive. When the brand score is greater than or equal to 3, the effect of consumption level on Xianyu's choice is negative. The increase in brand score will make consumers with high consumption levels less likely to choose to buy second-hand goods on the Xianyu platform.

Similarly for the regression model based on the apparel dataset, we partial derivative with respect to the consumption level C_i, we can get

$$\frac{\partial \mathscr{L}(PC_{ij})}{\partial C_i} = -0.32 - 0.06IB_{ij} \tag{3.12}$$

The values of the coefficient β_5^a and α_1^a in this model are also both significantly different from 0 ($p < 0.05$), indicating that the influence of consumption level and the interaction term are both statistically significant on the platform choice decision of consumers. The difference from the results of the digital product dataset is that both β_5^a and α_1^a are less than 0, which means that the impact of consumption level is negative in all cases of brand scores. And under most conditions, the negative effect of the consumption level in the apparel products based model is stronger than that of digital products.

In summary, the impact of consumption level on platform choice is affected by product type and brand score. Consumption level shows a more substantial negative effect when faced with apparel products with higher emotional value than those with higher functional value products. At the same time, the increase in brand score will also amplify the negative impact of the increase in consumption level on Xianyu's choice odds.

Brand Socre

Next, we compared the change trend of Xianyu purchase proportion with product brand score under two different datasets. We can find out from Figure 3-7 that,

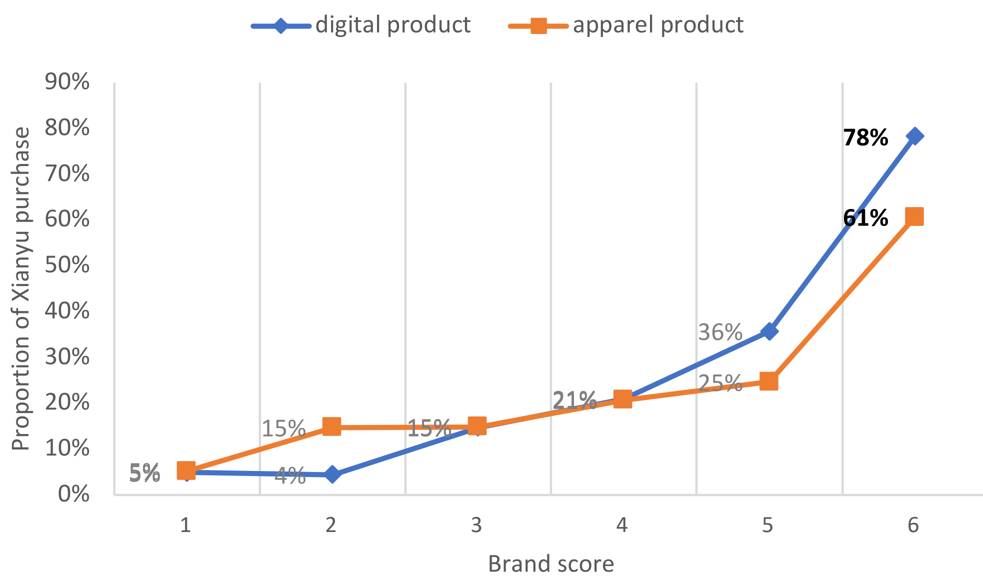


Figure 3-7 Xianyu Purchase Proportion Change with the Consumption Level

whether it is a product with high emotional value or a product with high functional value, the increase in brand score will increase consumers' preference to buy this product on the Xianyu platform. The results in the regression equation also reflect this phenomenon. For the digital product dataset, the coefficient β_6^d of the commodity brand score in the regression model equal to 1.6 and is significantly different from 0 ($p < 0.001$). At the same time, we can get the partial derivative of the brand score and get

$$\frac{\partial \mathscr{L}(PC_{ij})}{\partial IB_{ij}} = 1.6 - 0.19C_i \tag{3.13}$$

For the value range of consumption level from 1 to 5, the value of formula 3.13 is always greater than 0. This shows that consumers of different consumption levels tend to buy products with high brand value on Xianyu when selecting second-hand electronic items. But this kind of positive effect is weaker for a higher consumption level buyer.

At the same time, we can also get the partial derivative of the brand score for the model based on the apparel dataset. We can get

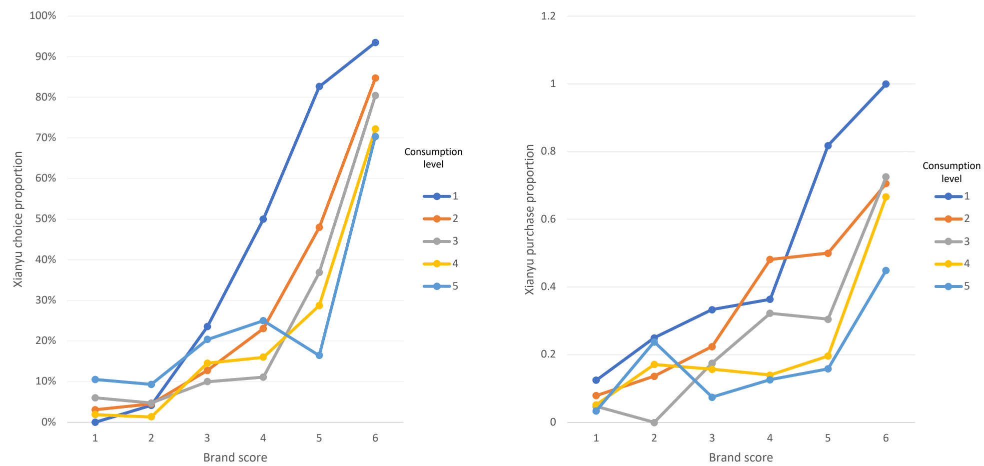
$$\frac{\partial \mathscr{L}(PC_{ij})}{\partial IB_{ij}} = 0.78 - 0.06C_i \tag{3.14}$$

It can be found that the conclusion is the same as that in the digital product dataset, but it should be noted that

$$\beta_6^d - \alpha_1^d C_i > \beta_6^a - \alpha_1^a C_i, \text{for } C_i \in [1,5] \tag{3.15}$$

This shows that consumers are more sensitive to the brand score of high functional value products when purchasing second-hand products on the Xianyu platform.

In summary, the brand score of the product has a significant positive impact on the consumer's decision to purchase on the Xianyu platform. This effect is moderated by the consumer's consumption level and product type. Figure 3-8 shows that regardless of the kind of product, consumers with a lower consumption level are more sensitive to brand scores. In other words, consumers with a low consumption level prefer the Xianyu platform purchases products with high brand scores. At the same time, comparing Figures 3-8 (a) and (b), it can be seen that the slope of each broken line in (a) is generally greater than that in (b). This means the positive impact of the brand score on Xianyu's purchase probability is more significant for products with high functional value, like digital items.



(a) Digital product dataset (b) Apparel product dataset

Figure 3-8 The Impact of Brand Score under Different Consumption Level

3.5 Chapter Summary

In this chapter, we mainly analyse the factors influencing consumers' decisions to purchase in Taobao or the second-hand market Xianyu. The factors mainly include the two dimensions of user characteristics and product characteristics. We comprehensively applied different kinds of data analysis methods like data visualisation techniques, hypothesis testing, and logistic regression analysis methods, et. The main conclusions include the following:

1) For user-related characteristics, first of all, age is an important factor affecting consumers' platform choices. The age showed a U-shaped effect of rather decreasing and then increasing the Xianyu platform choice odds. The descending stage is from under 18 to 24 years old, and the ascending stage is from 24 to over 45. Second, the effect of gender is also significant, but the effect

direction is moderated by commodity type. For products with high functional value, men will show a higher purchase preference on the Xianyu platform, while women will deliver a higher interest in buying high emotional value products on second-hand platforms

2) The commodity type is an important variable affecting consumers' platform choices. We use digital products and apparel products as representatives to study the impact of high functional value products and high emotional value products on platform choice. The results show that consumers are more inclined to buy products with high emotional value on the Xianyu second-hand platform. Simultaneously, the product category will moderate the impact of consumption level and product brand rating on platform selection. Commodities with a high emotional value will intensify the adverse effect of augmented consumption levels on the purchase rate for the Xianyu platform, whereas those with a high functional value will intensify the positive effect of enhanced brand scores on the purchase rate for the Xianyu platform. Generally speaking, consumers prefer to buy functional products with high brand scores on the Xianyu platform, while high purchase power consumers are not very interested in second-hand products with high emotional value.

3) The improvement in consumption level will reduce the probability of consumers choosing the Xianyu platform to buy second-hand goods. Improving product brand scores will increase the likelihood of consumers choosing the Xianyu platform. However, these two variables will interact with each other. Consumers with low consumption levels prefer to buy products with high brand scores on the Xianyu second-hand platform. For users with a high consumption level, changes in brand scores have relatively little impact on their decision to choose a platform.

Chapter 4 Let's talk: Factors affecting online buyers and sellers engagements on Xianyu platform

4.1 Research Question Description

In the discussion of Chapter 3, we analysed the factors influencing consumers to choose the Xianyu platform for online second-hand shopping. This chapter will explore consumers' decisions and behaviours when they enter the Xianyu App to buy a product. Generally, when consumers enter the Xianyu App, they will first search for or browse the products they are interested in on the homepage. Then buyers will obtain preliminary information about the products and the sellers on the product introduction page. Buyers leave the introduction page if they are not interested in the product they are viewing. If the buyer shows the intention to purchase after an overview of the preliminary information, they will choose to communicate with sellers for more details about the products. Whether to conduct a transaction is usually the result of the communication between the sellers and buyers.

As we can see from Figure 4-1, the whole process can be divided into two stages. The first stage is the buyer browsing information to initiate a chat with the seller, and the second stage is from chatting to completing the transaction. This is a process of considering the information of buyers and sellers. In the research process, not only the characteristics of users as buyers need to be analysed, but also the influence of sellers' information needs to be considered. In this chapter, we will discuss the first stage and mainly analyse the factors that affect the buyer's decision to chat with the seller. The generation of chat behaviour represents that the buyer has a relatively strong purchase intention for the product, so the behaviour of initiating a chat can also be understood as the generation of purchase intention. The impact factors mainly include the seller's information, such as credit level and historical transaction records, and product information, such as the length of the title and the product description.

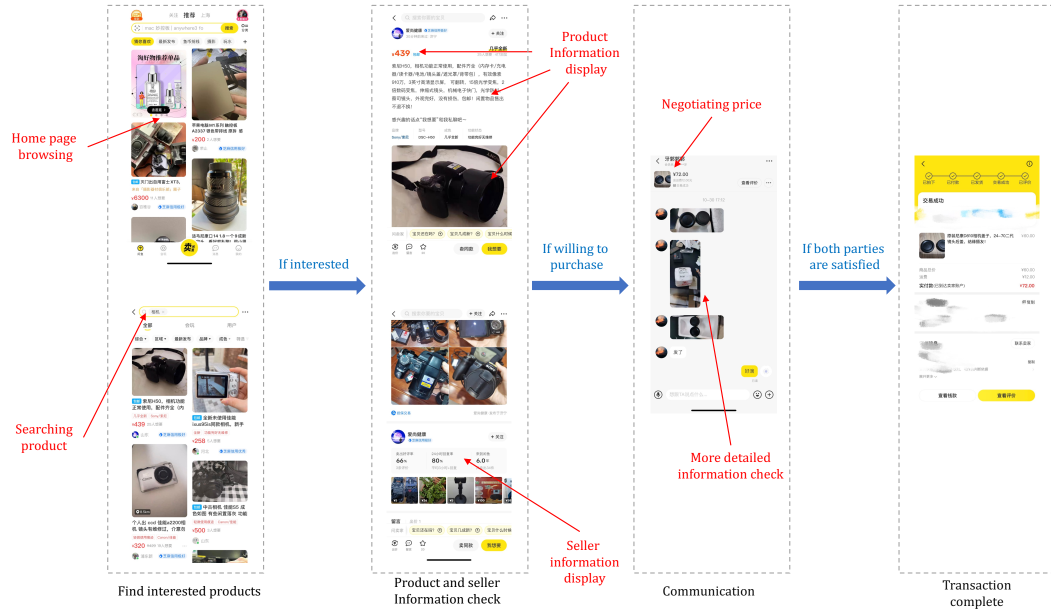


Figure 4-1 The Basic Process of Purchasing Products on the Xianyu App

4.2 Data and Variables Introduction

Our data records the subsequent behaviour of buyers entering the product detail page over a period of time. Due to a large number of browsing and searching behaviours of buyers, which are hard to record, the first arrow "**If interested**" conversion processes in Figure 4-1 are not recorded in the data. Each piece of data records a browsing event on the details page. The data records the personal information and historical transaction records of the buyer who browsed the product and the seller who posted the product. Our data also document the title of the product and the number of words in the description, and the result of whether the browsing was converted into a chat.

Due to the limitation of data availability, our analysis in this section is mainly aimed at the factors that affect consumer behaviour of choosing contact with the seller after browsing the product detail page ("**If willing to purchase**" arrow in

Figure 4-1). This conversion process reflects that the buyer is greatly interested in the product and expresses the intention to purchase it. In the environment of online second-hand transactions, the generation of consumers' willingness to purchase is the result of careful consideration of factors such as risk, price, and the value of the product (Z. Li et al., 2013; E. J. Park et al., 2012). Hence, our data records two main factors that may influence consumers' willingness to purchase and chat: buyer perception of risk and buyer perception of product information richness.

4.2.1 Buyer Perception of Risk

On the online second-hand platform, the process of trading goods can be regarded as risky behaviour for both parties. For the buyer, since the product cannot be directly checked by themselves, the actual condition of the product after purchase may be different from the seller's description. This situation of consumers suffering losses due to product information descriptions not matching the actual products was an important reason for people to doubt e-commerce in the early days of Internet shopping (Paynter & Lim, 2001). Although first-hand commodity shopping platforms like Taobao have carried out strict management and inspection on this behaviour of deceiving consumers and achieved good results, this kind of fraud situation still exists in the second-hand market. Therefore, buyers on the second-hand platform usually have to fully assess the risks before deciding to buy to decide whether to make a purchase. There are four variables related to buyer risk perception recorded in our data.

The Positive Review Rate of Sellers

The Xianyu platform will record the number of products sold by the seller and the previous evaluation information given by other buyers and sellers after transactions. This information gives buyers a reference basis to judge whether the seller they are facing is reliable and honest. Therefore, the seller's historical sales volume in the past 180 days S_i, the total number of reviews received by the seller TR_i (both the buyer and the seller can evaluate each other after the transaction is over, so the evaluation information here is not only the after-sales evaluation but the evaluation of the user's overall performance on the Xianyu platform), and the total number of positive reviews received by the seller TPR_i are the information recorded in our data set. By dividing the total number of positive reviews TPR_i by the total number of reviews TR_i, we can get an important indicator reflecting the user's credit rating on the Xianyu platform, the positive review rate PR_i

$$PR_i = \frac{TPR_i}{TR_i} \tag{4.1}$$

Since the equation 4.1 has no meaning when $TR_i = 0$, we define

$$PR_i = \text{'no enough historical review information'}$$

when $TR_i = 0$. At the same time, the number of pieces of evaluation information may also affect the buyer's risk judgment. Therefore, both the number of sellers' historical review information TR_i and the positive review rate PR_i should be considered as variables that may affect the results of chat conversion.

The Type of Xianyu Users

In the last chapter, we mentioned two types of users on the Xianyu platform. The first type is professional users with large sales or purchases number. Although the Xianyu platform is a second-hand trading platform focusing on C2C, there are still many professional users activated on the platform to get profit by selling and purchasing second-hand products. And their accounts are more like a privately-run second-hand goods store. The second type is amateur users with a relatively small volume of sales and purchases. They mainly sell their own private second-hand goods or purchase second-hand goods for their own use. Professional users' ability to acquire and analyse second-hand product information far exceeds that of amateur users. This gap in experience may further amplify the impact of information asymmetry in the second-hand market on transaction fairness. Therefore, an amateur user may feel distrustful or dominated when facing a professional user. On this basis, we divide buyers and sellers into three levels of users, users with little experience, ordinary users with some experience, and professional users.

Our data records buyers' behaviour browsing second-hand commodity posts; each browsing record is a piece of data. For the buyer who browsed the posts, our data records the number of products he or she purchased on the Xianyu platform in the past 180 days. For the seller who posted the post, our data records the number of products he or she sold on the Xianyu platform in the past 180 days. It should be noted that our data only has historical purchase data for buyers but no historical sales data. Correspondingly, for sellers, we only have their historical sales data but no historical purchase data. Therefore, we can only judge whether the buyer is experienced in purchasing second-hand items online but cannot determine whether the user is also experienced in sales and vice versa. Overall, we use the buyer's purchase volume in the past 180 days P_i to find out if the buyer is an experienced buyer and the seller's sales volume in the past 180 days S_i to find out if the seller is an experienced seller. We denote the type of buyer as BT_i and the type of seller as ST_i, and the rules shown in 4.2

$$BT_i = \begin{cases} \text{little experience} & P_i = P_0 \\ \text{ordinary} & 0 < P_i < 100 \\ \text{professional} & P_i > 100 \end{cases}, ST_i = \begin{cases} \text{little experience} & S_i = 0 \\ \text{ordinary} & 0 < S_i < 200 \\ \text{professional} & S_i > 200 \end{cases} \tag{4.2}$$

The value of the thresholds used to classify users is given by the business experts of the Xianyu platform, where the purchase volume threshold is equal to 100 and the sale volume threshold is equal to 200.

In addition, we suspect that the experience level of the seller may have an impact on the buyer's choice, so we added another variable TM_i about the matching situation about the type of buyer and seller. There are 9 different situations for the type matching of buyers and sellers, such as **little experienced buyer with little experienced seller** and **professional buyers and ordinary seller**, etc. Since there are too many types of variables, we will not give specific definition expressions. What needs to be known is that the variable types include combinations of three different types of buyers and three different types of sellers.

The City Match of Users

As the largest second-hand trading platform in China, Xianyu used to have two built-in community models, a community classified by geographical location and a community based on interest types. Members in both communities gradually build trust among individuals by exchanging common interests, and values (Y. Lu et al., 2010). Although this kind of community has been canceled in the current Xianyu App, it can be seen that the same geographical location may reduce the risk perception of buyers. In addition, the situation in the same city also allows offline transactions for buyers and sellers, greatly reducing the risk of transactions. It may encourage buyers to have a stronger desire to buy and convert it into chat behaviour with sellers. Our data records the geographical location information of buyers and sellers. By judging whether they belong to the same city, we can get a new variable CM_i

$$CM_i = \begin{cases} \text{Yes} & \text{If buyer and seller live in the same city} \\ \text{No} & \text{If buyer and seller live in the different city} \end{cases} \tag{4.3}$$

The Gender Match of Users

By observing the description information when selling goods on the Xianyu platform, we can often find that sellers use words like "girls use it for themselves" when selling goods. From this information, some consumers may prefer second-hand goods sold by girls because they think that women cherish their belongings more so that they can buy newer second-hand goods. This is also a kind of psychology for buyers to reduce risk expectations. On the other hand, in terms of social attributes, gender differences may lead to differences in the positive degree of social interaction between men and women. Therefore, we wanted to explore whether chat conversion rates differ when users of different genders act as buyers and sellers. Hence, we define a variable GM_i to describe the different gender match situations

$$GM_i = \begin{cases} \text{mSmB} & \text{If seller is Male and buyer is Male} \\ \text{mSfB} & \text{If seller is Male and buyer is Female} \\ \text{fSmB} & \text{If seller is Female and buyer is Male} \\ \text{fSfB} & \text{If seller is Female and buyer is Female} \end{cases} \tag{4.4}$$

4.2.2 Buyer Perception of Product Information Richness

As we mentioned above, the product information that users can obtain on second-hand platforms is very limited. In addition, the product's wear degree and whether the products' functions remain intact are different due to various factors such as product use age, purchase channels, and previous users' usage habits, et al. Therefore, it is difficult for general users to judge whether the browsed goods meet their needs when the seller only provides limited information.

Therefore, adequate product description information can make buyers better perceive the product's value and how it matches their expectations. Our dataset has certain limitations in the collection of product description information. In Figure 4-1, we can see complete product information with the product price, product title content, product description, and pictures. However, our data only collects information about the number of words in the product title and the product description, and the text content and picture information are not retained in the data. Therefore, we can only use the number of words in the product title TL_i and the number of words in the product description DL_i to represent the richness of product information. In fact, there is no option to enter a title when publishing a post in the Xianyu App. The title displayed on the homepage is actually the first 18 characters of the product description before the new line (as shown in Figure 4-2).

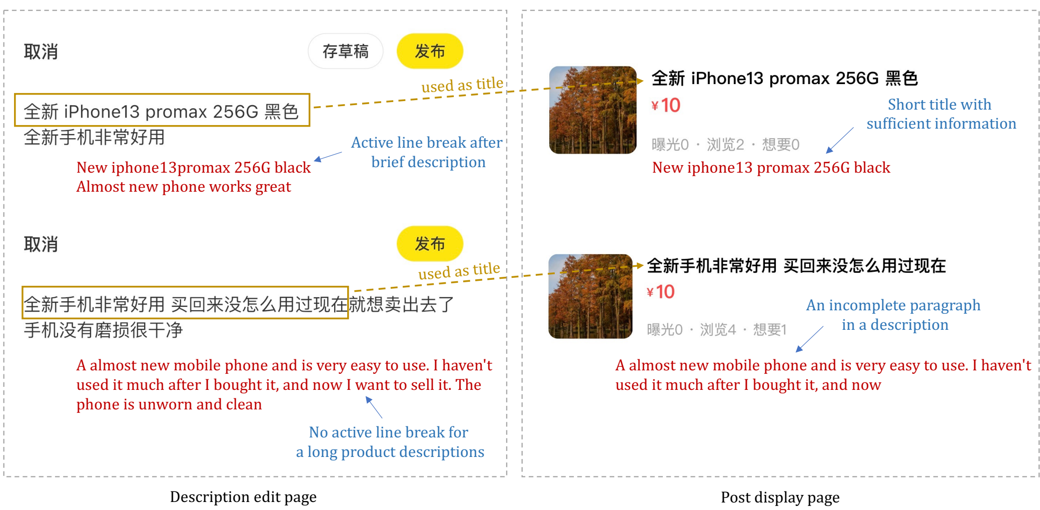


Figure 4-2 Generation of Post Titles for Second-hand Products on Xianyu

Therefore, one strategy for better display titles is to briefly introduce the product's characteristics in the first 18 characters of the description and then break the line. This strategy is helpful in displaying a more readable and attractive title on the homepage. Therefore, if a seller uses such a strategy to make the product title more formal, buyers may get more useful information from the title and are more likely to convert to a chat with the seller later. Hence, we define a new variable GT_i that represents whether the poster intentionally makes the title more attractive

$$GT_i = \begin{cases} \text{Suitable} & \text{If title length } TL_i <= 18 \\ \text{Unsuitable} & \text{If title length } TL_i > 18 \end{cases} \tag{4.5}$$

where the number of words in the product title TL_i indicates the length of the first paragraph of the product description before the line break.

4.3 Regression Model Building

4.3.1 Descriptive Statistics of Variables

The data used for data analysis contains a total of 3913 pieces of record. We randomly selected about 2000 entries from successfully converted and failed converted records from the whole data set, respectively. Some of the records lack essential information we need in the analysis, such as gender, etc., which are discarded from our data. The final data contains 2101 records of buyers initiating chats to sellers and 1812 records of buyers abandoning further communication. Due to the large volume of overall data (above million levels), 3913 randomly selected data basically do not have the problem of user duplication. It can be considered that the buyers and sellers in the data are unique individuals. In this section, we will first give the descriptive statistical results of the relevant variables and then give a detailed quantitative analysis of each variable.

First, we start to analyse the user's Xianyu APP usage experience. As we have introduced before, we only know the buyer's purchase information and the seller's sales information. Therefore, it is assumed in our analysis that a user's identity as a buyer or seller is separated and not affected by each other in our analysis. As seen from Table 4-1, ordinary users account for the vast majority of the buyer or seller groups. It reached 81.9% in the buyer group and 67.1% in the seller group, slightly lower. It is worth noting that the proportion of professional sellers in the sellers' group is significantly higher than that of professional buyers in the buyer group, reaching 24.9%. This result shows that although the Xianyu platform is a second-hand trading platform focusing on C2C, the proportion of merchant groups is not so small as to be negligible.

Table 4-1 The Descriptive Statistics for User Type

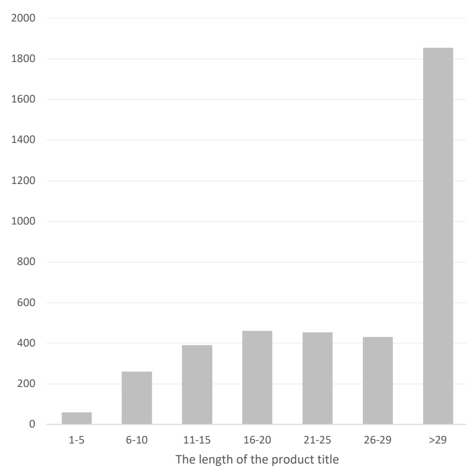
	Little experience	Ordinar	Professional
Buyer	477 (12.2%)	3205 (81.9%)	231 (5.9%)
Seller	314 (8.0%)	2624 (67.1%)	975 (24.9%)

Then, we can see from Table 4-2 that, regarding gender, the number of men in the buyer group is 2345, and the number of women is 1568. At the same time, there are 2208 males and 1705 females in the seller group. Generally speaking, the proportion of male users is higher than female users, which is also in line with the analysis results in Chapter 3. Meanwhile, the ratio of women in the seller group is slightly higher than in the buyer group.

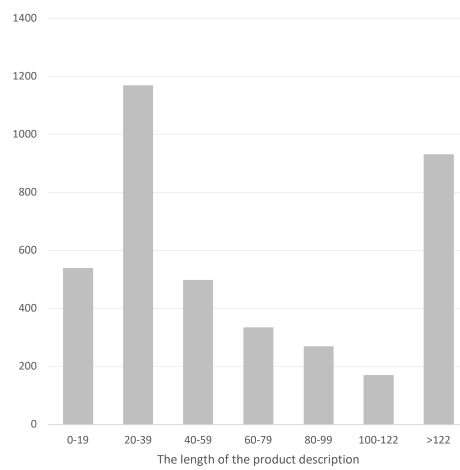
Table 4-2 The Descriptive Statistics for User Gender

	Buyer Group	Seller Group
Male	2345 (59.9%)	2208 (56.4%)
Female	1568 (40.1%)	1705 (43.6%)

Regarding city matching, 3327 pieces of the browsing records occurred when the buyers and sellers were not in the same city, which is about 85% of the total data set. Finally, we give the histograms of their frequency distributions for the two variables characterizing product description information, the number of words in the product title TL_i and the number of words in the product description DL_i. Because the Xianyu App has a maximum character limit for the text data records of second-hand commodity posts. Titles with more than 30 words and product descriptions with more than 123 words can only record the parts that are less than the threshold. Therefore, we can only use > 29 and > 122 to indicate the word count of longer titles and descriptions.



(a) Title Length Distribution



(b) Description Length Distribution

Figure 4-3 The Distribution of Different Lengths of Product Titles and Description

From Figure 4-3, we can find out that the frequency of the length of the title reaches a small peak at 16-20 characters and then has a downward trend. However, the number of posts with more than 29 words titles is still large, and it is guessed that TL_i is distributed with fat tails. This phenomenon also exists in the histogram of DL_i. The frequency of description words reaches a peak at 20-39 characters and then gradually declines, but there are still many posts with more than 123 characters in the product descriptions.

Through the above qualitative analysis and graphic display, we can find that the variables discussed in Section 4.2 correlate with the buyer's final behaviour of initiating a chat. Next, we will conduct a more in-depth and rigorous discussion on the relationship between variables by establishing a regression model.

4.3.2 Model Building and Coefficient Estimation

The dependent variable of the regression model is whether the buyer initiated a chat during this browsing time CC_i. And the definition of other independent variables is shown in Table 4-3 below. The relevant definitions of the variables have been introduced in detail in section 4.2.

Table 4-3 The Description of Variables

Variable Name	Variable Description	Notation
Chat conversion	Whether the buyer initiates a chat with the seller (Yes or No)	CC_i
Buyer type	The purchase experience level of the buyer (1: Little experience, 2: Ordinary, 3: professional), defined by 4.2	BT_i
Seller type	The sell experience level of the seller (1: Little experience, 2: Ordinary, 3: professional), defined by 4.2	ST_i
User type match	A combination of buyer types and seller types, including 9 different categories, for example the professional Buyer with ordinary Seller	TM_i
Positive review rate	The overall evaluation level of sellers on the Xianyu platform calculated by 4.1	PR_i
Review count	The total number of sellers' historical review information	TR_i
City match	Whether the buyer and seller live in the same city (Yes, No)	CM_i
Gender match	The gender match of sellers and buyers, with four different situations defined by 4.4	GM_i
Title strategy	Whether the title of the product well designed, defined by 4.5	GT_i
Description length	The number of words in the product post description	DL_i

Before modeling, we need to conduct a multicollinearity test on the variables to ensure that there is no significant correlation between different variables. We used the `vif()` command of `car` package in the `R` language to do the multicollinearity test, and the results are shown in Table 4-4 below. We can see that the value of Variance Inflation Factor(VIF) of each variable are smaller than 2, which Indicates that there is no significant collinearity between the variables.

Table 4-4 The Description of Variables

Variable Name	VIF	Degrees of Freedom(DF)	VIF$\times \left(\frac{1}{2\times \mathrm{DF}}\right)$
Buyer type	1.018	1	1.0090
Seller type	1.44	1	1.20
Positive review rate	1.14	1	1.067
Review count	1.23	1	1.11
City match	1.019	1	1.0095
Gender match	1.041	3	1.0067
Title strategy	1.030	1	1.015
Description length	1.15	1	1.072

Then, we considered building two logistic regression models to fit the binary dependent variable CC_i, and in both model initiate a chat is the positive outcome in our model. In model 4.6, we consider the effects of buyers type and sellers type independently , hence the variables BT_i and ST_i are added to the model. $\boldsymbol{\beta_7}$ is a vector containing three values since the gender matching situation GM_i is a categorical variable with four different types, also as $\boldsymbol{\gamma_1}$ is a vector. The coefficient α_1 Indicates the impact of the seller's positive review rate on the chat conversion rate when there is sufficient seller information. Because only when the seller's historical evaluation quantity $TR_i \neq 0$ is the seller's historical positive review rate a meaningful variable. Hence, the introduction of this interaction term ensures that the effect of PR_i is interpretable.

$$\mathscr{L}(CC_i) = \beta_0 + \boldsymbol{\gamma_1} BT_i + \boldsymbol{\gamma_2} ST_i + \beta_1 TR_i + \beta_2 GT_i + \beta_3 DL_i + \beta_4 CM_i + \boldsymbol{\beta_5} GM_i$$
$$+ \alpha_1 TR_i \times PR_i + \varepsilon \tag{4.6}$$

In model 4.7, we consider the moderating effect of seller type on the influence of buyer type, so we change the variable considering user type to the match of the user type TM. It can be seen that the difference between the two models is only in consideration of the influence of user type, and the settings of other variables are the same.

$$\begin{aligned}\mathscr{L}(CC_i) = \beta_0 + \boldsymbol{\gamma_3} TM_i + \beta_1 TR_i + \beta_2 GT_i + \beta_3 DL_i + \beta_4 CM_i + \boldsymbol{\beta_5} GM_i \\ + \alpha_1 TR_i \times PR_i + \varepsilon\end{aligned} \tag{4.7}$$

The coefficient of the regression model were estimated by the `glm()` function in `R`. We can use the value of Akaike information criterion(AIC) to judge which of the two models can better fit the data (Akaike, 1974). We found that the AIC value of model 4.6, which does not consider the interaction between user types, equals 4377.8. While the model 4.7, which considers the interaction between buyer and seller types, has an AIC value of 4321.6. Since AIC of 4.7 smaller than AIC of 4.6, the model 4.7 fit the data better and the results are more explanatory. We give the estimated value of the coefficient of model 4.7 in the following Table 4-5.

Table 4-5 Regression Result of Model 4.7

Characteristic	Coefficient	[1]95%CI	p-value	[2]OR
User type match				
Little Buyer with Little seller	-	-	-	-
Little Buyer with Ordinary seller	-0.212	$(-1.00, 0.651)$	0.6	0.809
Little Buyer with Professional seller	-1.37	$(-3.39, 0.108)$	0.11	0.253
Ordinary Buyer with Little seller	-0.105	$(-0.968, 0.804)$	0.8	0.90
Ordinary Buyer with Ordinary seller	2.59	$(1.95, 3.35)$	**< 0.001**	13.3
Ordinary Buyer with Professional seller	3.63	$(2.96, 4.42)$	**< 0.001**	37.7
Professional Buyer with Little seller	-12.3	$(-285, -243)$	> 0.9	0.000
Professional Buyer with Ordinary seller	3.90	$(3.16, 4.74)$	**< 0.001**	49.3
Professional Buyer with Professional seller	5.06	$(3.67, 6.99)$	**< 0.001**	157
Review count	0.023	$(0.009, 0.038)$	**0.002**	1.02
Title strategy				
Unsuitable	-	-	-	-
Suitable	0.236	$(0.069, 0.405)$	**0.006**	1.27
Description length	0.000057	$(-0.002, 0.002)$	> 0.9	1.00
City match				
Not same city	-	-	-	-
Same city	0.015	$(-0.197, 0.228)$	0.9	1.01
Gender match				
Female buyer Male seller	-	-	-	-
Male buyer Female seller	-0.379	$(-0.647, -0.113)$	**0.005**	0.685
Female buyer Female seller	-0.304	$(-0.554, -0.057)$	**0.016**	0.738
Male buyer Male seller	-0.383	$(-0.617, -0.152)$	**0.001**	0.682
Review count $\times$ Positive review rate	-0.023	$(-0.038, -0.009)$	**0.002**	0.978

1. CI = Confidence Interval **2**. OR = Odds Ratio

4.4 Discussion

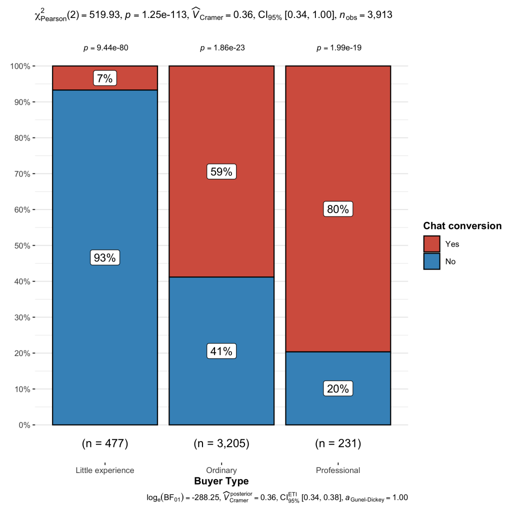
In the previous section, we obtained the impact of different variables on the final chat conversion results by establishing a regression model. This section will comprehensively analyse the data performance and regression results of different variables and discuss their influence.

4.4.1 The Impact of Users' Type

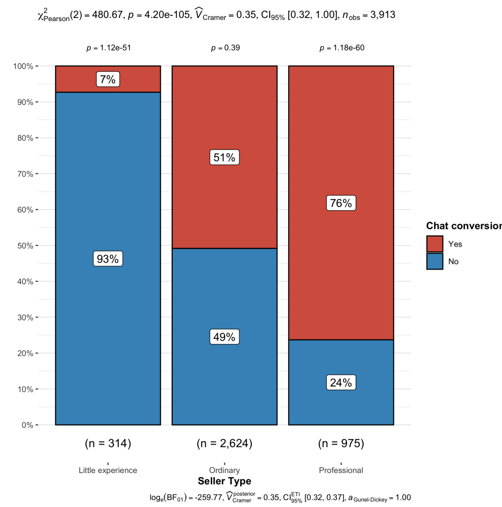
Hypothesis: The type of buyer and seller does not affect the final chat conversion

In the previous introduction, we divided buyers and sellers into three users with different experience levels based on the transaction data in the past 180 days, namely buyers (sellers) with little experience and ordinary buyers with some experience (sellers), and experienced professional buyers (sellers), and we can see formula 4.2 for specific definitions. In this subsection, our discussion focuses on how the experience of buyers and sellers affects the final chat conversion results and whether these two variables have interactive effects.

First, we analyse the impact of the types of buyers and sellers by the data performance, respectively. From Figure 4-4 (a), we can see that with the increase in the historical experience of buyers and buyers, the final chat conversion rate has a significant upward trend.



(a) Impact of Buyers' Type



(b) Impact of Sellers' Type

Figure 4-4 The Impact of Users' Type on the Chat Conversion

This shows that buyers with more experience will be more active in initiating chats with sellers during the browsing process, showing a stronger willingness to buy. Buyers will prefer sellers with more historical sales. This may be because the limited historical information that amateur sellers can provide makes consumers more aware of the risks in the transaction process. Professional sellers have been operating their accounts in Xianyu App for a long time, and more transaction information provides them with more credit guarantees, which makes them more popular in the market.

Next, we discuss about the interaction effect between the buyer and seller types. We plot the chat conversion rate change with the experience level of the seller under different buyer types, as shown in Figure 4-5.

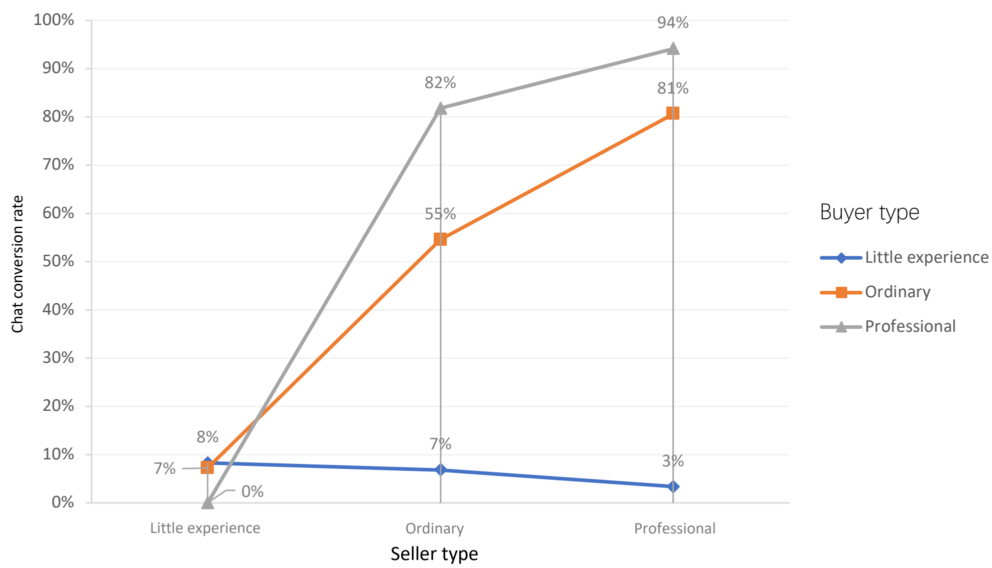


Figure 4-5 The interaction effect of seller type and buyer type

We can see that when the buyer's experience level is ordinary or professional, the chat conversion rate really increases as the seller's experience increases. The result matches the explanation in the previous section about the increase in sales volume leading to the increase in credit level. However, it can be observed from Figure 4-5 that when the buyer has little experience in using the Xianyu app, the increase in seller sales does not lead to an increase in chat conversion rate. It will lead to a certain decline trend in the conversion rate in this situation. This situation may be because inexperienced buyers lack enough judgment on the risks of second-hand market transactions and are worried that experienced sellers may deceive them in the transaction by some unknown method. Therefore, they will be more inclined to communicate with sellers with similar experience levels as themselves.

Finally, the above analysis can also be confirmed in the regression model results. We want to compare the effect of seller type when the buyer's type is little experience, ordinary and professional respectively, which we cannot get directly from the result of Table 4-5. We simply modify the regression model by adding a new variable T_i, which is equal to 1 when TM_i is equal to 'little experience buyer with ordinary seller', and equal to 0 otherwise. We multiply this variable with TM_i to get a interaction term $TM_i \times T_i$ into model 4.7.

$$\begin{aligned}\mathscr{L}(CC_i) = \beta_0 + \boldsymbol{\gamma_3} TM_i \times T_i + \beta_1 TR_i + \beta_2 GT_i + \beta_3 DL_i + \beta_4 CM_i + \boldsymbol{\beta_5} GM_i \\ + \alpha_1 TR_i \times PR_i + \varepsilon\end{aligned} \tag{4.8}$$

The new model does not change the results of other variables, but only changes the benchmark of the variables in TM_i to be the situation of 'little experience buyer with ordinary seller', and we can get the impact of seller type changes when the buyer is in little experience. Use the same method, by changing the definition of T_i as following two description:

1. equal to 1 when TM_i is equal to 'ordinary experience buyer with ordinary seller', and equal to 0 otherwise.

2. equal to 1 when TM_i is equal to 'professional experience buyer with ordinary seller', and equal to 0 otherwise.

We can get the impact of seller's type as showing in Table 4-6. We can see that for buyers with little Xianyu purchase experience, the increase in seller experience has a negative effect on the chat conversion rate. The odds of initiating chats for the little experience buyer when facing similarly inexperienced sellers is 1.23 times of when facing ordinary sellers, but the odds decrease to 0.313 when facing with professional sellers. But this negative effect is not statistically significant while the p-value of the two coefficients are $0.61 > 0.05$ and $0.151 > 0.05$ respectively. However when the buyer type is ordinary buyer, the seller's experience has a significant positive effect on chat conversion. The odds of initiating chats for the ordinary buyer when facing little experience sellers is 0.087 times of when facing ordinary sellers, but the odds goes up to 3.62 when facing with professional sellers. This positive effect is statistically significant while the p-value of the two coefficients are

Table 4-6 Regression Result of Model with Different Benchmark of Buyer's Type

	Characteristic	Coefficient	p-value	OR
(1)	Little Buyer with Little seller	0.212	0.610	1.23
	Little Buyer with Ordinary seller	-	-	-
	Little Buyer with Professional seller	-1.162	0.151	0.313
(2)	Ordinary Buyer with Little seller	-2.439	**< 0.001**	0.0872
	Ordinary Buyer with Ordinary seller	-	-	-
	Ordinary Buyer with Professional seller	1.287	**< 0.001**	3.622
(3)	Professional Buyer with Little seller	-1.616	0.951	0.199
	Professional Buyer with Ordinary seller	-	-	-
	Professional Buyer with Professional seller	1.159	0.125	3.187

(1). for the model $T_i = 1$ when TM_i = Little experience buyer with ordinary seller
(2). for the model $T_i = 1$ when TM_i = Ordinary buyer with ordinary seller
(3). for the model $T_i = 1$ when TM_i = Professional buyer with ordinary seller

both smaller than 0.001. Finally, when the buyer is a professional user, the effect of the seller's experience level is also positive but not significant.

We can reject the hypothesis raised at the beginning of this section through the above analysis and regression results. Both buyer and seller types can significantly affect the final chat conversion rate. Experienced buyers will be more proactive in initiating chats. The influence of seller type is changed in the different types of buyers. For inexperienced buyers, the effect of increasing the seller's sell experience is insignificant but has a negative trend. However, increasing sellers' experience will lead to a significantly higher chat conversion rate for ordinary buyers. Finally, for professional buyers, the change in seller experience has become less influential.

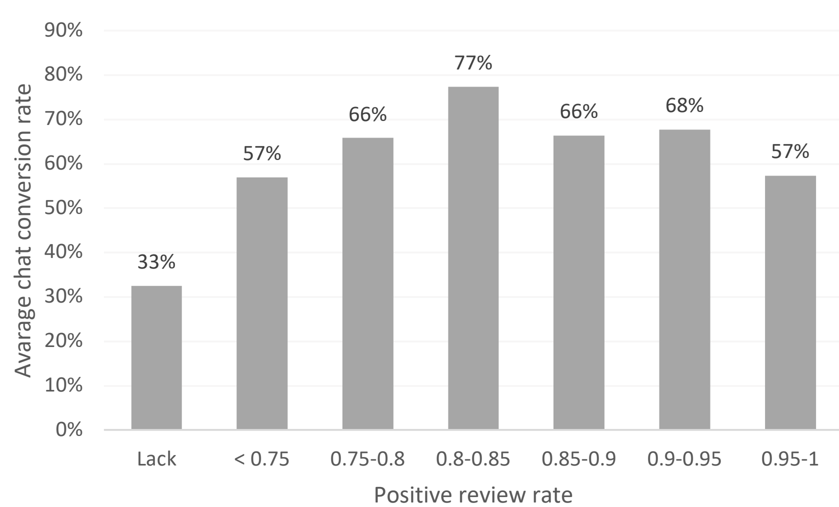
We believe the changes in risk perception and judgment of buyers mainly cause this situation. Inexperienced buyers have almost no ability to judge risks, while experienced sellers have a dominantly advantage in their ability to trade second-hand products. Therefore, they may prefer to communicate with sellers who are also as inexperienced as themselves. On the contrary, professional buyers' rich experience allows them to handle the risks in the transaction well, so they have the confidence to reach a satisfactory transaction result with any type of seller. At this time, the influence of the type of seller is not significant. Ordinary buyers have a certain sense of risk but cannot handle every situation as well as professional sellers, so they trust sellers with more transaction records during the transaction process.

4.4.2 The Impact of Users' Review Record

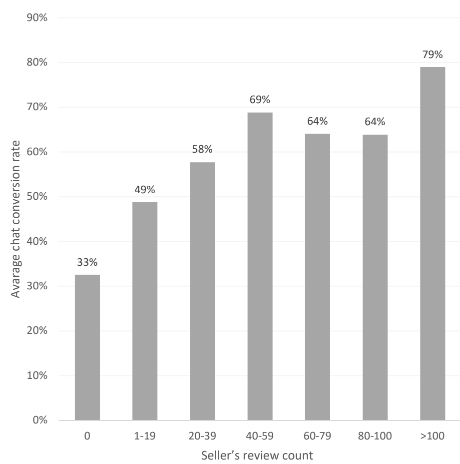
Hypothesis: The seller's historical evaluation information has no effect on the final chat conversion rate

The seller's positive review rate (given in formula 4.1) is an important indicator for assessing the transaction risk. In Figure 4-6, we give the chat conversation under different sellers' positive review rate, where **Lack** means lack of enough information. As the seller's historical positive review rate increases, the final chat conversion rate shows a trend of rising first and then falling.

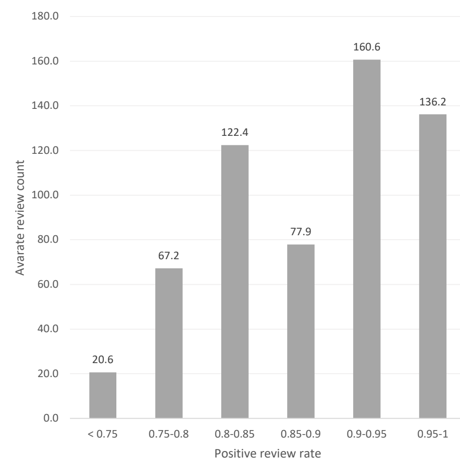
Figure 4-6 Chat conversion change within different sellers' positive review rate



In order to explain this phenomenon, we need to introduce another variable: the total number of historical reviews received by the seller (including positive and negative reviews) TR_i. As another important dimension of historical evaluation information for sellers, more evaluation data can give buyers more references. At the same time, more historical evaluations can also improve the stability of the positive and negative review rates. Therefore, these two variables should have a common influence on the final transformation result. We divided sellers' historical evaluation quantity into seven levels in the data display section. Then, we can get each level's average chat conversion rate, as shown in Figure 4-7 (a) below.



(a) Impact to Chat Conversion



(b) Impact to Positive Review Rate

Figure 4-7 Impact of Sellers' Review Count

Unlike the influence of the seller's historical positive review rate, the historical review count positively correlates with the chat conversion rate in each quantity level.

We need to notice at the same time that for those users with higher favorable ratings, their average count of evaluations is also higher, showing a positive correlation (as shown in Figure 4-7 (b)). Therefore, the inverted U-shaped change trend of the chat conversion rate when the positive review rate changes from low to high is likely to be mixed with the influence of the number of historical reviews. In the stage of positive review rate changes from 0 to 0.85, the positive effect of increasing the number of reviews is greater. In the 0.85 to 1 stage, the negative impact of the favorable historical rate is more significant.

We can find a more definite answer from the regression model results for the joint influence of these two variables. The coefficients of $\beta_1 = 0.023$ and $\alpha_1 = -0.023$, these two coefficients are significantly non-zero(p-value < 0.05), indicating that the seller's historical evaluation information has a significant impact on the final chat conversion, and we can reject the hypothesis given in the beginning of the section. Then, by taking the partial derivative of the variable TR_i, we can get

$$\frac{\partial \mathscr{L}(CC_i)}{\partial TR_i} = 0.023 - 0.023 PR_i \tag{4.9}$$

Since the value of the seller's historical positive review rate PR_i is between 0 and 1, the value of the expression 4.9 is always positive. This result shows that sellers with more sufficient historical evaluation information are more likely to increase buyers' desire to purchase. At the same time, $\alpha_1 = -0.023$ shows that a higher positive review rate will decrease the chat conversion rate when given a certain review count.

4.4.3 Impact of Product Title and Description

Hypothesis: The title length and product description length of the seller's second-hand product post will not affect the final chat conversion rate

First, we give the relationship between whether the seller controls the title within 18 characters, which is a suitable title, and the number of chat conversions in Table 4-7. To test if these two variables are independent, we can also apply `chisq.test` and `fisher.test` command to the table, and we can get both of the p value of the test bigger than 0.05 (p value of `chisq.test` equal to 0.18 and p value of `fisher.test` equal to 0.17).

Table 4-7 The Impact of Title Length on Chat Conversion Rate

	Conversion	Not conversion	Conversion rate
less or equal to 18	549	439	55.6%
greater than 18	1552	1373	53.1%

Although we can find out from the data performance in Table 4-7 that the chat conversion rate of posts with less than 18 characters in the title is relatively higher, the hypothesis test results cannot reject the null hypothesis that the chat conversion rate is independent of the title length of the post. This result differs from our previous conjecture, but the results after controlling other variables, which are given in Table 4-5, give more convincing results. It shows that $\beta_2 = 0.236$, which is not equal to 0 significantly, suggesting we should reject the hypothesis that title length will not affect the chat conversion rate. A shorter and more readable title will significantly increase the final chat conversion rate.

Next, we drew a histogram describing the distribution of chat conversion rate change within the product description length for the impact of product description length. From Figure 4-8 we can find that, as the number of product description words increases, the chat conversion rate also gradually rises. And the p-values of the `chisq.test` less than 0.001, indicating that the product description length significantly impacts the buyer's purchase intention. This result shows that the longer the product description and the richer the information it provides, the more it can attract consumers' interest in purchasing the product.

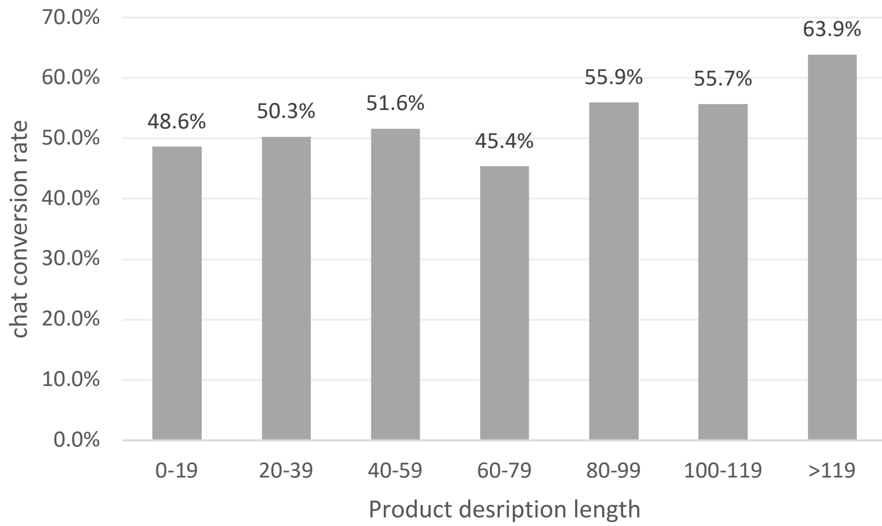


Figure 4-8 The Chat Conversion Rate Change with Product Description Length

However, at the same time, we can see from Figure 4-9 that more experienced sellers will post product posts with longer text descriptions.

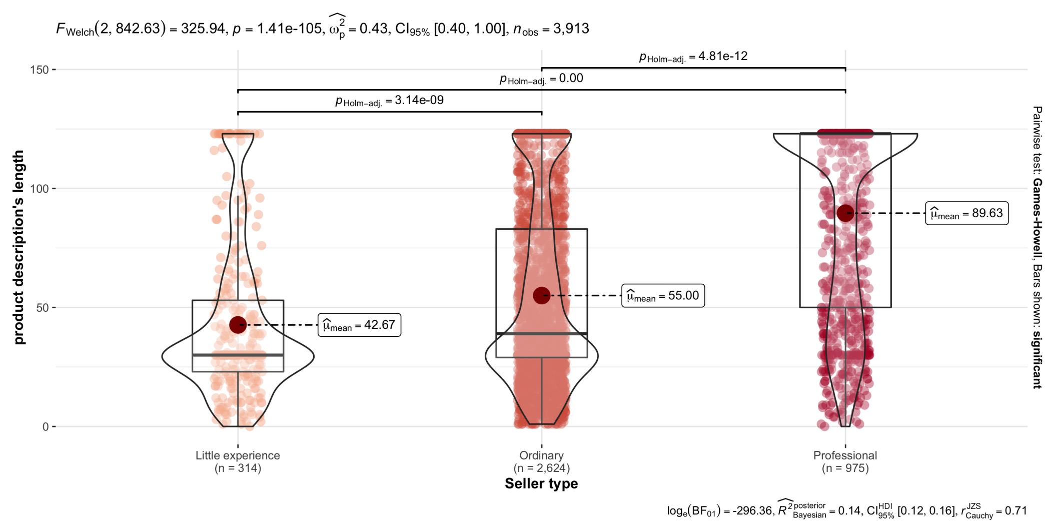


Figure 4-9 Product Description Length Change with Seller Type

Therefore, the positive relationship between the length of product post descriptions and chat conversion rate may be just a pseudo-correlation. The coefficient of the regression model gives the final result, $\beta_3 = -0.000057$ is insignificant, which indicates that the length of the product post description does not significantly impact the chat conversion rate when the seller type is controlled. This result proves our conjecture that the correlation between product post description length and chat conversion rate is a pseudo-correlation, and we cannot reject the hypothesise that post description length will not affect the chat conversion rate.

4.4.4 Impact of Information Match of Seller and Buyer

Hypothesis: The personal characteristics match will not affect the final transaction conversion rate

First, for the gender matching of buyers and sellers, we counted the chat conversion rate when GM_i takes four different values. As shown in Table 4-8, female buyers seem to initiate chats more actively than male buyers.

Table 4-8 The Impact of Gender Match on Chat Conversion Rate

Buyer gender	Seller Gender	Conversion	Not conversion	Conversion rate
Male	Male	834	811	50.7%
Male	Female	365	335	52.1%
Female	Male	345	218	61.3%
Female	Female	557	448	55.4%

Applied the `chisq.test` and `fisher.test` to the data, we can get that the gender matching of buyers and sellers does have an impact on the conversion of chats (p-value of both tests less than 0.001). Through the conditional contingency table, we can also conduct a more detailed analysis of this gender impact pattern. Do the following test with changed given condition and dependent variables

$$\begin{aligned} H_0 &: \text{Given that buyer is male, chat conversion is independent from seller's gender} \\ H_1 &: \text{Given that buyer is male, chat conversion is dependent from seller's gender} \end{aligned} \tag{4.10}$$

then, we can get the test result in different situations from the results in the above table and the regression analysis results, we can see that when the buyer is a woman, the probability of initiating a chat is significantly higher regardless of whether the seller is a man or a woman (p-value< 0.05). When the seller is male, the odds of chat conversion for a male buyer are 0.682 times the odds for a female buyer. When the seller is female, the odds of chat conversion for a male buyer are $0.685/0.738 = 0.93$ times the corresponding odds for a female buyer.

Table 4-9 Test of the Impact of User Gender on Chat Conversion

Fixed condition	Dependent variable	`chisq.test` p value	`fisher.test` p value
Buyer is male	Seller's gender	0.55	0.53
Buyer is female	Seller's gender	0.028	0.025
Seller is male	Buyer's gender	<0.001	<0.001
Seller is female	Buyer's gender	0.20	0.18

In addition, this result suggests that the seller's gender will impact the buyer's intention to initiate a chat, but this effect is only significant in the female buyer group. Female buyers are more likely to initiate chats with male sellers. The regression model's coefficients can also prove this interpretation's correctness. The odds ratio given in Table 4-5 suggests that compared with the case of female buyers and male sellers, the conversion rate when both buyers and sellers are female is only 0.78 times that of the former, which is significantly smaller. In summary, we can say that female buyers will initiate chatting more actively, especially when the gender of the seller is male.

Finally, we show the chat conversion when buyers and sellers are in the same city and different cities (Table 4-10). The chat conversion rate in the same city is significantly lower than in different cities (p value of `chisq.test` and `fisher.test` are both less than 0.001). The coefficient of the city matching variable in the regression model has a value of $\beta_4 = -0.015$, which is in-significantly not equal to 0. It indicates that the result of city matching has no significant impact on the final chat conversion rate.

Table 4-10 Chat Conversion in Same City and Different City Situations

	Conversion	Not conversion	Conversion rate
Same city	315	271	46.2%
Different city	1497	1830	55.0%

The results of the multiple regression model show that the same city cannot significantly affect the results of the chat conversion rate. This may be due to the bias caused by the lack of information about the first conversion process in Figure 4-1. As shown in Figure 4-10, the buyer has already filtered the product posts in the first conversion process. Buyers are more likely to favor the same city transaction

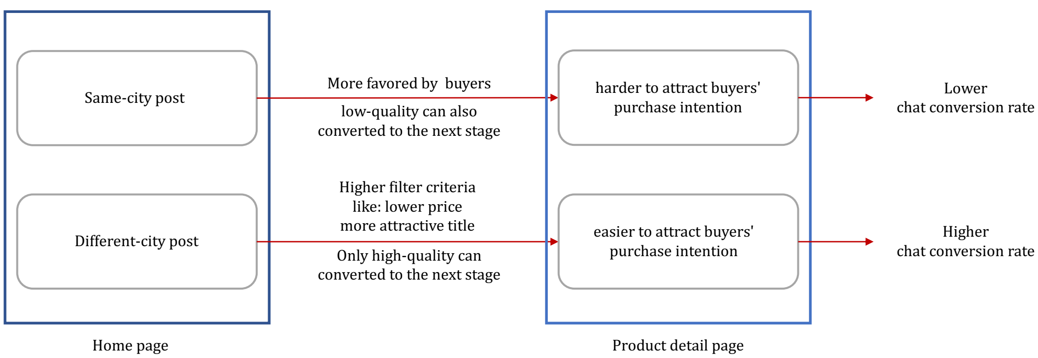


Figure 4-10 Possible Explanations for Lower Same-city Chat Conversion Rates

post in the first conversion process. Hence, buyers will view more low-quality same-city product detail pages in the second conversion process, leading to a lower chat conversion rate. On the contrary, different-city trading posts have a higher quality standard in the first filter process (including considering information such as price, title description, etc.), and it is more difficult to enter the stage of chat conversion. Therefore, different-cities product posts in the chat conversion process are usually of higher quality, and it is easier for buyers to have the willingness to purchase.

4.5 Chapter Summary

In this chapter, we study the influencing factors of buyers on the Xianyu platform who actively initiate chats after browsing products. We mainly analyse the influence of factors such as the seller's historical information, characteristics matching of sellers and buyers, and information richness of product descriptions. The main conclusions include the following:

1) For transaction risk perception, the historical transaction experience information of buyers and sellers in the Xianyu second-hand market jointly affects the final chat conversion. Very inexperienced buyers prefer to communicate with sellers as inexperienced as they are in second-hand trading. Experienced buyers prefer sellers who are also more experienced. At the same time, the richness of the seller's historical evaluation information and the historical positive review rate also impacts the buyer's willingness to purchase. Buyers prefer sellers with rich historical evaluation information, but an excessively high positive review rate may reduce the final chat conversion rate.

2) The gender match of buyers and sellers can significantly affect chat conversion rates. The chat conversion rates of female buyers are significantly higher than male buyers. In addition, the influence of the gender of the seller is statistically significant when the buyer is female, and female buyers will prefer to initiate chats with male sellers. The impact of geographic location matching is not significantly positive or negative. This result is different from our prior knowledge, and the reason for this phenomenon may be the bias caused by missing part of the information.

3) The techniques used by sellers when posting second-hand items also have an impact on buyers' purchasing intentions. When composing titles, sellers need to pay attention to the conciseness of the title, keeping it within a specific character count to maintain its readability. This can significantly increase consumers' interest in the product and translate into further communication behavior with the seller. However, the length of the item description does not have a significant effect on the final chat conversion outcome. Nevertheless, more experienced sellers tend to write longer product descriptions, allowing consumers to access more comprehensive product information.

Chapter 5 Predicting Second-Hand Transaction Conversion by Combining Customers' Behaviours and Customers' sentiments: A machine learning approach

5.1 Research Question Description

The social attributes of second-hand transactions are also one of the important reasons for attracting consumers to shop on second-hand platforms. During the communication process, the buyer and the seller confirm the details of the goods, negotiate the price, and enhance mutual trust, ultimately leading to the transaction's completion. Therefore, after we analysed the conversion process from browsing to chatting in the previous chapter, in this chapter, we will discuss the conversion process in which buyers and sellers of second-hand transactions successfully conclude a transaction after communication (the second arrow in Figure 4-1).

The transaction negotiation process on the Xianyu second-hand platform is carried out online. The tools for exchanging information between the two parties are mainly to send text messages, pictures, and videos. Typically, during the chat process, buyers and sellers inquire about more detailed information regarding the purchase process and the functionality of the product. Buyers use this information to determine whether the product meets their needs before deciding whether to make a purchase. Additionally, buyers and sellers evaluate transaction risks during their communication to determine whether to proceed with the transaction.

This chapter mainly analyses the text chat information between buyers and sellers. We mainly evaluate the emotions, motives, and strategies in the bargaining session displayed by the two parties during the chat process and analyse the impact of these factors on the final transaction completion. Therefore, we will first utilise methods such as machine learning to extract relevant features from the text, and then analyse the impact of the extracted features on the final transaction conversion.

Finally, we will combine the extracted features with other existing features in the data to predict the transaction outcomes.

5.2 Feature Extraction

5.2.1 Chat Emotion

In the second-hand trading market, buyers and sellers are strangers who do not know each other. A pleasant chat process can build trust between the two parties faster, which may be more conducive to completing the transaction. We randomly selected 19873 conversations from the database, all analysis and predictions in this section are based on this dataset. The most important information in the data is the chat records between buyers and sellers and whether the final transaction is completed. In addition, the data also includes variables that were analysed in the previous two chapters, such as the user's buying experience on the platform, consumption level, and the number of words in the product post title.

These selected dialogues are the results of filtering; we need to ensure that each chat session contains at least ten rounds of dialogue. Because if the number of rounds of the dialogue is too small, we cannot extract enough information from the conversation for analysis. We discuss the different ways of processing text information in two cases. In the first case, we focus on the Emojis appearing in the text. In the second case, we evaluate the overall sentiment of the text.

Emoji Usage

Emoji is is a kind of visual emoticon that is often used in web pages and chats. In Figure 5-1 shows several commonly used Emoji and their literal meanings, we can see that using Emojis in communication is a good way to express the current emotions and attitudes.

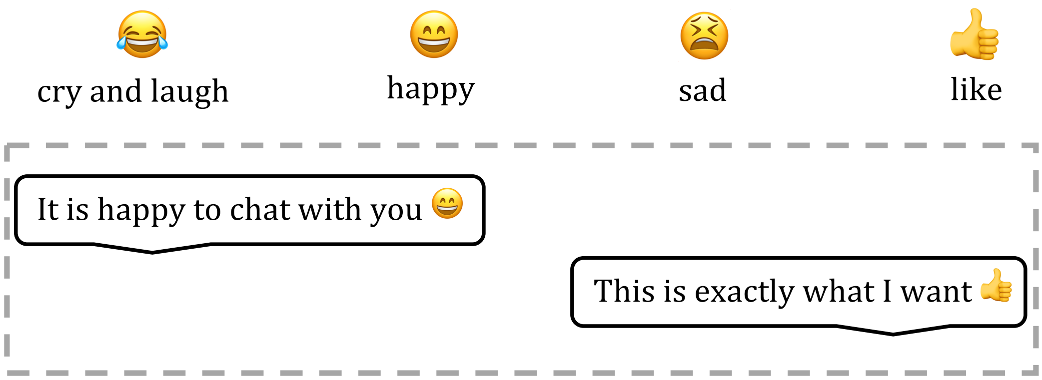


Figure 5-1 Some Commonly Used Emoji and their Literal Meanings

During chats on the Xianyu second-hand platform, buyers and sellers often use Emoji to express their emotions and opinions. In 11804 of the total 19873 conversations, buyers and sellers used different numbers of Emoji, and there are more than 100 types of Emoji used in the process. Analysing the impact of the use of each kind of Emoji on the final transaction is too complicated, and it is hard to get results about the influence of emotional attitudes in chat, which is what we are concerned about. Therefore, we counted the top 40 commonly used Emoji in the chat process and scored the emotional attitude of these Emoji through a questionnaire survey. We distributed questionnaires to 10 of the staff of Xianyu Apps, and gave each of the 40 Emoji three choices: positive, negative and neutral. Then, the positive, negative and neutral emotional attitudes are scored as 1, -1 and 0, respectively. So for each Emoji we get ten different emotion scores at the end of the survey according to each Staff's emotional feelings about these Emoji. Taking the average of these scores, we can get the average sentiment score of each Emoji ES_j, j for different kind of Emoji (details about the scoring of top frequencey used Emoji shown in Figure 5-2).

Next, we counted the number of times these 40 Emoji were used by buyers and sellers in the each conversation BN_{ij} and SN_{ij}, i for different conversations. Then, we can get the average Emoji based chat emotion score of buyers and sellers EEB_i

	Positive votes	Negative votes	Neutral votes	Emotion Score		Positive votes	Negative votes	Neutral votes	Emotion Score
	10	0	0	1		10	0	0	1
	10	0	0	1		10	0	0	1
	10	0	0	1		10	0	0	1
	9	0	1	0.9		9	0	1	0.9
	8	0	2	0.8		10	0	0	1
	10	0	0	1		10	0	0	1
	7	0	3	0.7		6	3	1	0.3
	7	1	2	0.6		6	3	1	0.3
	8	0	2	0.8		0	5	5	-0.5
	10	0	0	1		0	6	4	-0.6

Figure 5-2 The Emotion Score for the Top 20 Commonly Used Emoji

and EES_i

$$EEB_i = \frac{\sum_j ES_j \times BN_{ij}}{\sum_j BN_{ij}} \tag{5.1}$$

the calculation of sellers' socre EES_i is just same as 5.1. For buyers and sellers who do not use Emoji during the chat, this calculation 5.1 will not work. We define that when $BN_{ij} = 0$ or $SN_{ij} = 0$, there is correspondingly $EEB_i = 0$ and $EES_i = 0$, which shows emotional neutrality.

Overall Sentiment Score

In the previous part, we proposed using Emoji to judge the emotional state of buyers and sellers. Although this method can easily and quickly estimate the emotional tendency in the chat, not every user will use Emoji in the conversation, making the emotional status misjudge in situations without using Emoji. In order to solve this problem, we used a commercial sentiment analysis tool of Alibaba Group to analyse the chat content of buyers and sellers comprehensively. This tool is a Natural Language Processing(NLP) tool based on the Alibaba Cloud computing platform, which has a high accuracy of sentiment analysis. By entering text into the system, the platform will calculate three parameters about this text: the probability of the text expressing positive sentiment P_p, the probability of expressing negative sentiment P_n, and the text narrative is sentiment neutral P_0. These different probability values satisfy

$$P_p + P_n + P_0 = 1$$

A higher probability value of a particular emotion type indicates that this text is more inclined to that type. In order to measure the emotional state of a dialogue text, we define a new variable EC_i calculated by the following formula

$$EC_i = P_p^i - P_n^i \tag{5.2}$$

After using this expression, a larger positive EC_i indicated a stronger positive emotion in the text, and a larger absolute value of negative EC_i indicated a stronger negative emotion in the text. When the sentiment of the sentence is neutral, the values of P_p^i and P_p^i will be relatively small, which will cause the value of EC_i to tend to 0. Hence, a smaller absolute value of EC_i indicates that the text emotion tends to be neutral.

5.2.2 Chat Motivation

In this part, we want to find out the features of the motivation of buyers and sellers on what they say during the chat on the final transaction outcome. By analysing the chat text information recorded in the data, we define four motivations for buyers and sellers while chatting: bargaining, product details confirmation, product authenticity confirmation, and logistics information confirmation. It should be noted that the motivations described above can appear simultaneously in the same dialogue. This means we must judge whether the recorded chat data has the above four motives simultaneously. Since we should deal with a large amount of 19873 pieces of data, it isn't easy to classify all chat records by manual labeling. Therefore, we applied deep learning-based natural language processing techniques to classify chat text information.

Here, we use a very mainstream natural language processing method BERT to do the classification work (Devlin, Chang, Lee, & Toutanova, 2018). Of all available datasets, we labeled 3000 of them as training datasets and 500 as the validation dataset. After ten epochs of training, the classification accuracy of the model on buyer motivation on the verification set reached 85%, and the accuracy of classification of seller motivation reached 78%. Since increasing the amount of training cannot improve the performance of the model, even the phenomenon of overfitting will appear. We use the model trained for ten epochs as the optimal model and classify the remaining 16373 pieces of data. In the end, we obtained eight binary classification variables through the classification model, which are:

For **buyers**: whether buyer bargain in the chat, whether buyer check product detail in the chat, whether buyer confirm product authenticity in the chat, whether buyer check logistics information in the chat.

For **seller**: whether the seller bargain in the chat, whether the seller check product detail in the chat, whether the seller confirm product authenticity in the chat, whether the seller check logistics information in the chat.

5.2.3 Bargain Strategy

In the process of analysing the data, we found that, as one of the most important links in the chat process, buyers and sellers may use different strategies when bargaining. This strategy is mainly reflected in words used in the chat process between buyers and sellers. We use **B** to represent buyer and **S** to represent seller, in the following **Scenario 1**, both the buyer and the seller negotiate the price directly

B: Can you give me a lower price for this product?

S: No, at least 1000 Yuan.

In the following **Scenario 2**, buyers use stronger coercion strategy to bargain, and sellers choose to compromise.

B: Give me a lower price, or I'll have to buy elsewhere!

S: Okay, fine. I'll give you another 50 Yuan off.

In the last **Scenario 3**, the seller tactfully shows his difficulties in refusing the buyer's request for bargaining.

B: Can you sell it to me for 300 yuan?

S: This would really lose me a lot of money. I'm just a student with no income.

The above three cases are all conversations between buyers and sellers recorded in real data. We think that in Scenario 1, the buyer and the seller did not use any strategy. In contrast, the buyer used a threatening strategy in **Scenario 2**, and the seller used a strategy of showing weakness to win sympathy in **Scenario 3**.

We wonder whether the use of these strategies will affect the final transaction results. For example, in the second scenario, the seller compromises and lowers the product price when facing the buyer's threat strategy. Therefore, we used the same BERT approach as in the previous section to classify conversations that mentioned bargaining. The classified categories only include two cases: using strategic bargaining methods (such as the buyers in **Scenario 2** and the sellers in **Scenario 3**) and not using strategic bargaining methods (such as both of the buyers and sellers in **Scenario 1**).

5.3 Features' Impact on Transaction

5.3.1 Impact of Chat Emotion

Emoji Usage

In Figure 5-3, we show the changes in transaction conversion rates of buyers and sellers at different emotional levels. As we can see that, both the emotional scores of buyers and sellers significantly impact the final transaction rate, and we can also get sufficient evidence at the statistical level through `chisq.test` (the p value of the test for both buyers' emotional score and sellers' emotional score are less than 0.001). We can summarise that the Emoji based emotional level of communication between buyers and sellers during second-hand transactions significantly impacts the final transaction results. The more positive the emotional attitude shown during the chat, the more likely the second-hand commodity transaction will be concluded.

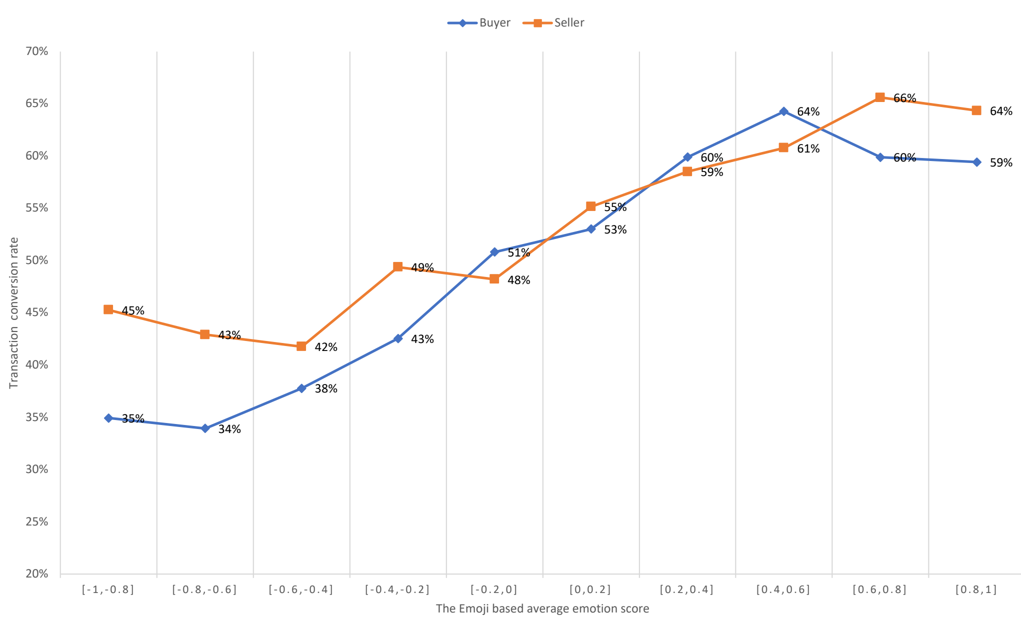


Figure 5-3 Transaction Conversion Rate at Different Emoji Based Sentiment Level

Overall Sentiment Score

First of all, we can see the distribution of chat emotions between buyers and sellers in Figure 5-4.

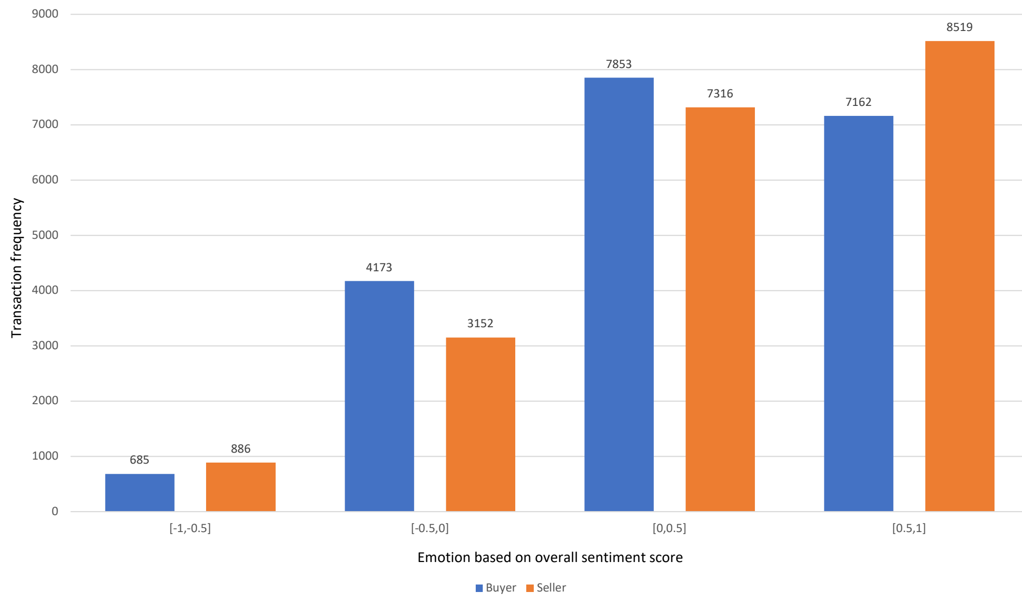


Figure 5-4 Chat Frequency at Different Emotional Levels

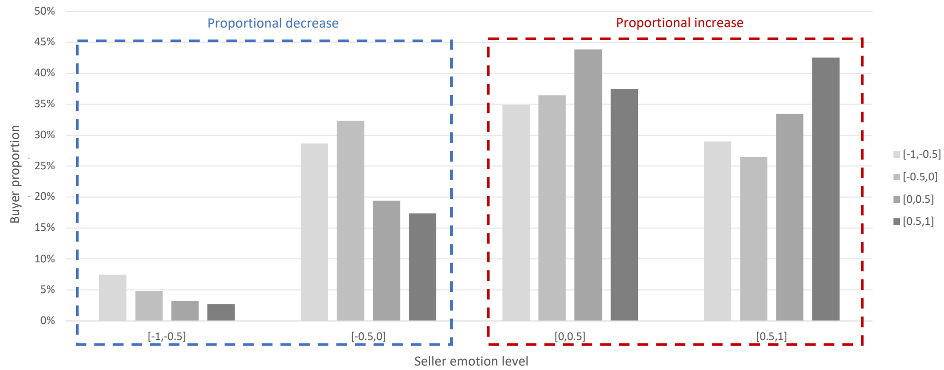
It can be seen that most users have positive emotions in the chat. Among them, the number of buyers in the relatively neutral emotional interval [-0.5,0.5) is more than that of sellers. But there are more sellers in the two more emotional intervals of [-1,-0.5) and [0.5,1]. This suggests that the buyer's emotional state is more neutral and calm during the transaction, but the seller may more probably have some emotionally expressive.

As participants in a transaction, the emotional levels of buyers and sellers are usually not independent of each other. That is to say that each other's behavior will affect their emotional status. To prove this conjecture, we can perform a hypothesis test on the contingency Table 5-1. The p value for `chisq.test` less than 0.001 indicates that the assumption that buyers' emotional states and sellers' emotional states are independent of each other is false.

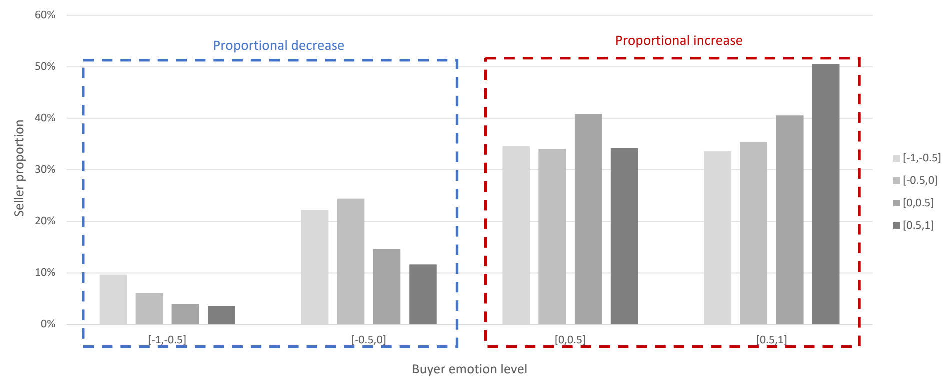
Table 5-1 The Interaction Effect of Buyers' and Sellers' Emotional States

		Buyer Emotional level			
		$[-1,0.5)$	$[-0.5,0)$	$[0,0.5)$	$[0.5,1]$
Seller Emotional level	$[-1,0.5)$	66	254	309	257
	$[-0.5,0)$	152	1018	1148	834
	$[0,0.5)$	237	1422	3209	2448
	$[0.5,1]$	230	1479	3187	3623

In Figures 5-5 we give a more intuitive evidence for this conjecture. For both buyers and sellers, the possibility of a positive emotional state increases with the increase of the emotional value EC_i of the other party. And the likelihood of a negative emotional state gradually decreases as the emotional state of the other party changes from negative to positive.



(a) Based on the Seller's Perspective



(b) Based on the Buyer's Perspective

Figure 5-5 The Interaction of Emotional State

Finally, we give the transaction conversion rates of buyers and sellers at different emotional levels. It can be seen from Figure 5-6 that no matter the buyer or the seller, when the sentiment level increases, the transaction conversion rate gradually increases.

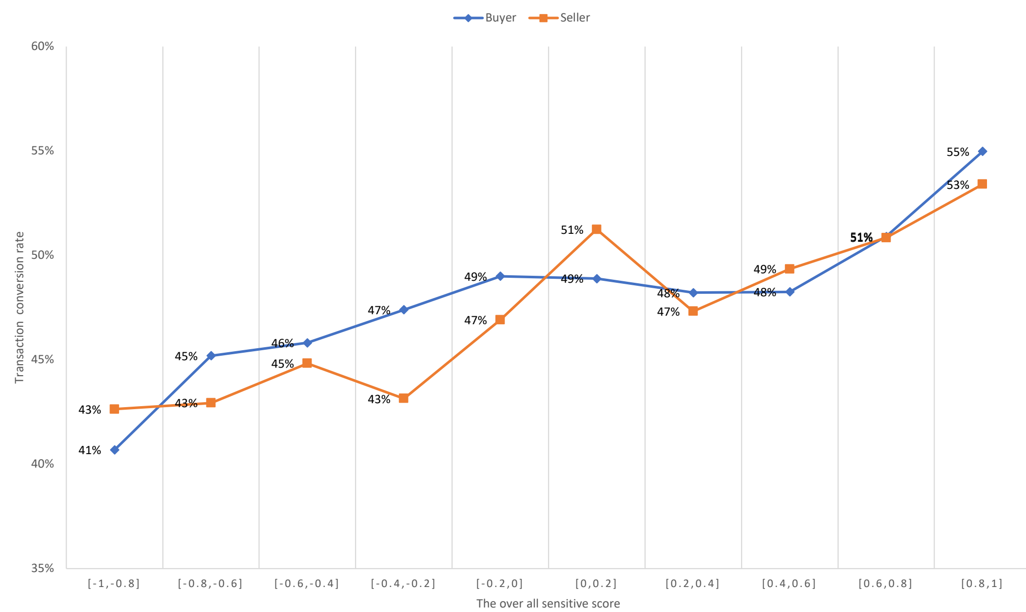


Figure 5-6 Transaction Conversion Rate at Different Overall Sentiment Level

From the results of above analyses we can conclude:

1) The emotional states of buyers and sellers are mutually influential. When one party has positive emotions, the other party is more likely to maintain a good emotional state. Conversely, when one partner's emotional state is not good, the other partner is more likely to have a negative emotional attitude.

2) Positive emotional attitudes have a positive impact on the results of transaction conversion, which is the same as our analysis results in the previous section.

5.3.2 Impact of Chat Motivation

In order to investigate the impact of motivational factors on the chat behavior of buyers and sellers, we compared the transaction conversion rates across four scenarios for each motivational characteristic: both parties have the same motivation, only the buyer has the motivation, only the seller has the motivation, and neither party has motivation. The result is shown in Table 5-2 below.

Table 5-2 The Impact of Different Behavior on Transaction Conversion Rate

	Both	Only Buyer	Only Seller	Neither
Bargain	44.0%	46.4%	55.1%	57.4%
Detail Check	44.2%	50.0%	51.6%	61.9%
Authenticity Confirm	52.3%	50.0%	50.2%	49.6%
Logistics Check	62.4%	58.0%	54.1%	30.7%

For bargain behavior, we can find out that the transaction conversion rate when both parties are bargaining is significantly lower than when both parties are not (the `chisq.test` with p value less than 0.001). The conversion rate when only one party is bargaining is just between them. When only the seller is bargaining, the conversion rate is significantly higher than the case when only the buyer is bargaining. It can be summarised that The more intense the bargaining between the two parties, the lower the transaction conversion rate. The same situation also occurs in the user behavior of confirming product details. The impact of detail check behavior on the transaction outcome is significant (the `chisq.test` with p value less than 0.001). The more buyers and sellers pay attention to the details of the product, the lower the probability that the transaction will be successfully completed.

Unlike the two behaviors discussed above, authenticity confirms behavior does not significantly impact the final transaction conversion rate. From the perspective of data performance, more concern about product authenticity in the second-hand transaction has a certain positive effect on the final conversion. Finally, we can see that the transaction rate will increase significantly when buyers and sellers mention logistics information (`chisq.test` is less than 0.001). If neither the buyer nor the seller mentions the logistics information of the products, the transaction rate is only 30.7%. Still, if one party mentions the logistics information, the transaction rate rises to more than 50%, and if both parties mention it, the transaction volume increases to more than 60%.

5.3.3 Bargain Strategy

It can be seen from Table Table 5-3 that about 23.7% of buyers will use strategic methods in bargaining, and using the strategy will bring them significantly better results (p value of the `chisq.test` less than 0.001). The transaction conversion rate of using the strategy is 49.4%, significantly higher than the value of 43.1% when not using the strategy. The same situation will happen when sellers use strategic haggling methods. About 28.6% of sellers will use strategic bargaining methods, and the transaction conversion rate will increase from 45.9% to 49.9% when bargaining strategically. The results of the contingency table test show that whether the seller uses a strategic bargaining method will significantly affect the final transaction result (p value of the `chisq.test` less than 0.001).

Table 5-3 Impact of Buyer Use Strategic Bargaining Methods

	Not Conversion	Conversion	Conversion rate
Buyer Strategically	1321	1288	49.4%
Buyer Not Strategically	4772	3611	43.1%
Seller strategically	1663	1655	49.9%
Seller Not Strategicall	4474	3793	45.9%

Next, we analysed how buyers and sellers use strategic approaches when they both bargain while chatting. First, we wanted to find out whether buyers and sellers use strategic bargaining method independently of each other. From the Figure 5-7, compared to buyers' average strategy usage rate of 23.7%, buyers' strategy usage rate increased to 50.1% when the opposite sellers also used bargaining strategies. In addition, when buyers use bargaining strategies, 41.4% of sellers will use bargaining strategies at the same time, which is also significantly higher than the average rate of 28.6%. This result suggests that the other party's behavior influences buyers' and sellers' use of bargaining strategies. When one party uses strategy, there is a higher probability that the other party will also use strategy instead of simply giving a price.

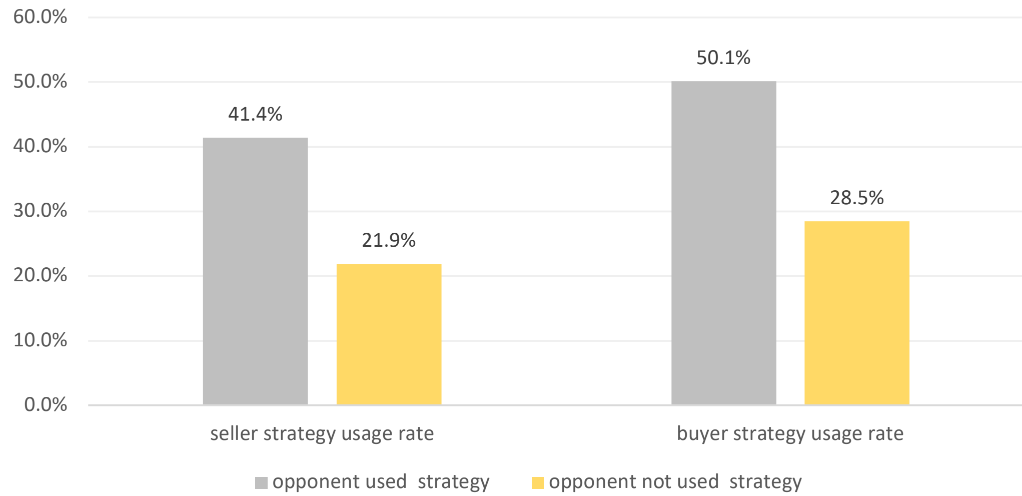


Figure 5-7 The Interaction of Strategic Bargaining Behaviors

5.4 Transaction Result Forecast

In section 5.2, we extracted features related to user chat sentiment, chat motivation, and bargain strategies from the text. In section 5.3, we conducted statistical analysis on the impact of these feature variables on the final transaction conversion rate and found that all three features have a significant impact on the final conversion result. In this section, we will build multiple machine-learning models to predict transaction outcomes by incorporating the parameters extracted from the chat information and other variables into the models. Finally, we will compare the performance of different models and analyse the importance of variables.

5.4.1 Introduction and Preprocessing of Data

The data we use is still the data analysed in the previous two sections, which includes 19873 entries, of which 9925 are successful transactions in the second-hand market. In this section, we do not use all the data for predictive modeling but only focus on the transaction records of two types of products: mobile phones and beauty products. These two categories of products are popular categories in the second-hand market, with 7555 entries for mobile phone transaction records and 4947 entries for beauty product transaction records.

The data includes a total of 28 variables, including 13 personal information variables of buyers and sellers, 2 variables related to the product transaction posts posted by sellers, 12 variables extracted from the chat between buyers and sellers, and a dependent variable. The specific introduction of variables can be found in the description in Table 5-4. It should be noted that for the variables related to the sentiment status during the chat between buyers and sellers, we only selected the overall sentiment score variable obtained from the machine learning model, instead of choosing the sentiment score obtained from Emojis. Since these two variables describe the same feature, we only selected one of them to be included in the model.

Before building the prediction model, variable preprocessing is necessary. Since some variables in the data contain missing values, it is necessary to fill in these missing values first. Here, we choose to use the K nearest neighbor method to fill in the missing values by prediction.And we use the `preProcess(method='knnImpute')` function of the `caret` package in `R` to do this job (Kuhn, 2008). Next, we normalise continuous variables and one-hot encoding on categorical variables. Use one-hot encoding to convert categorical variables into as many binary (1 or 0) variables as there are categories. In `caret`, one-hot-encodings can be created using `dummyVars()`. Just pass in all the features to `dummyVars()` as the training data, and all the factor columns will automatically be converted to one-hot-encodings. Finally, we use the k-fold cross-validation method to divide the data into training and testing sets, here, we choose $k = 10$. The overall flow of data processing and modeling is shown in Figure 5-8.

Table 5-4 The Variables in the Forecast Model

Variable Category	Variable Name	Variable Description
Dependent variable	Transaction conversion	Whether the transaction complete (Yes or No)
User characteristic variable	Gender	The gender (Male or Female) of buyer (seller)
	Age	Continuous variable of age of buyer (seller)
	Consumption level	Consumption level of buyer (seller) increase from 1-5
	Xianyu experience	The purchase amount of buyer (seller) on Xianyu in past 180 days
	Historical review	The historical review amount of buyer (seller) on Xianyu
	Positive review	The historical positive review amount of buyer (seller) on Xianyu
	City match	Whether the buyer and seller live in the same city (Yes or No)
Chat feature variable	Sentiment score	The overall sentiment score of buyer (seller) while chat
	Bargain	Whether buyer (seller) bargain while chat (Yes or No)
	Detail check	Whether buyer (seller) check product detail while chat (Yes or No)
	Authenticity confirm	Whether buyer (seller) confirm product authenticity while chat (Yes or No)
	Logistics check	Whether buyer (seller) check logistics information while chat (Yes or No)
	Bargain strategy	Whether buyer (seller) use strategic bargain method while chat (Yes or No)
Product post variable	Title length	The number of words in the product post title
	Description length	The number of words in the product post description

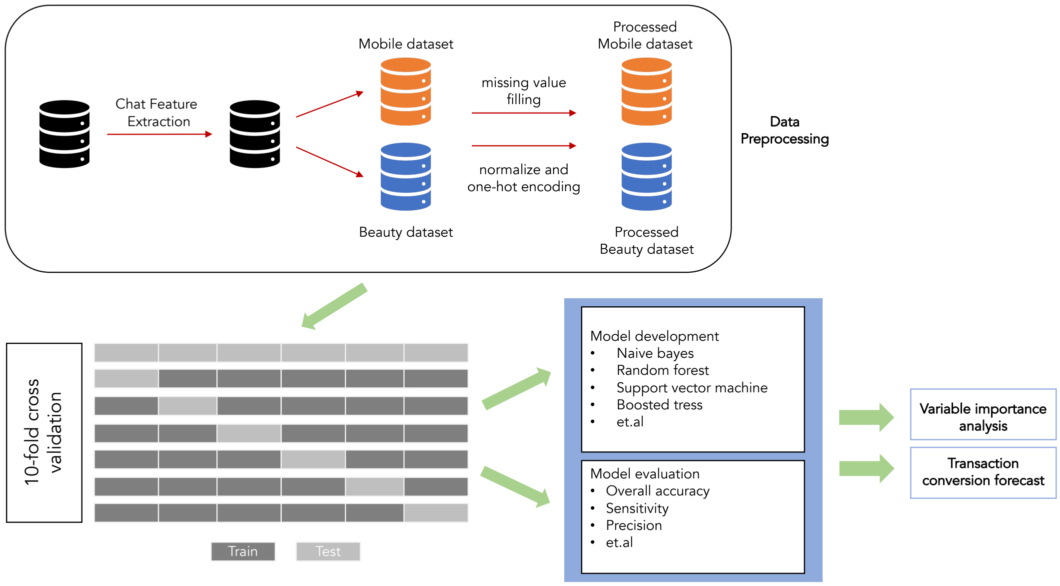


Figure 5-8 The Process of Data Process and Modeling

5.4.2 Classification Model

We used nine different machine learning methods for modeling, including Naive Bayes (D. D. Lewis, 1998), K-Nearest Neighbors (Zhang, 2016), Random Forest (Breiman, 2001), Support Vector Machine (SVM) (Hearst, Dumais, Osuna, Platt, & Scholkopf, 1998), Classification and Regression Tree (CART) (R. J. Lewis, 2000), Bagged CART (Breiman, 1996), Extreme Gradient Boosting (XGB) (T. Chen et al., 2015), Boosted Tree (Elith, Leathwick, & Hastie, 2008) and Bagged AdaBoost (Freund, Schapire, et al., 1996). Method like Naive Bayes, K-Nearest Neighbors and SVM are very basic and commonly used machine learning models, which is well applied in many classification problems. These models have a good balance between accuracy and complexity.

The Naive Bayesian method can combine the prior probability and posterior probability, which avoids the subjective bias of using prior probability alone and the overfitting phenomenon of using sample information alone. The Bayesian classification algorithm can get a high accuracy based on a large dataset, and the algorithm is relatively simple at the same time.

Unlike the probability-based approach of the Naive Bayes algorithm, the K-nearest neighbors (KNN) algorithm mainly relies on calculating distances between samples. By comparing the distances between different sample points, the KNN algorithm selects the k-nearest points in the labeled set and decides the category of the sample point by voting. It can be seen that the KNN approach is simple and easy to implement and therefore has a wide range of applications in practical environments.

Support vector machine (SVM) is a commonly used supervised learning model in classification and regression analysis. Given a set of training examples, each training example is labeled as belonging to one or the other of two categories. The SVM training algorithm creates a model that assigns new instances to one of the two categories, making it a non-probabilistic binary linear classifier. The SVM model represents instances as points in space, mapping points of different classes to different sides of the classifier as much as possible. Then, new instances are mapped into the same space, and the predicted category is based on which side of the margin they fall on. The difference between support vector machine and linear regression is the introduction of the kernel function $k(\cdot)$ in Equation 5.3. The introduction of kernel functions and kernel tricks allows the classifier to map inputs to a high-dimensional feature space, thus better handling nonlinear classification problems.

$$f(x) = b + \sum_{i} \alpha k(x_i, x_i^T) \tag{5.3}$$

CART is also a very useful classification model, but a single tree model often suffers from the overfitting problem. Therefore, many advanced models based on tree models have been developed, such as random forest and extreme gradient boosting. These models coordinate decisions from multiple decision trees to obtain more accurate results and can also avoid the problem of overfitting. In addition, when splitting nodes during tree construction, the chosen split is no longer the best split among all features, but rather the best split among a random subset of features. Due to this randomness, the classification results of each tree classifier in a random forest may introduce bias. However, due to averaging, the variance of the results is also reduced, which is usually sufficient to compensate for the increase in bias caused by the sub-sampling.

We use these nine different methods to make predictions for both mobile phone and beauty product datasets, respectively.

5.4.3 Model Evaluation

We used six different indicators to evaluate the prediction model, including Sensitivity, Specificity, Precision, Accuracy, F1 score, and Matthews correlation coefficient (MCC). These metrics are defined based on the confusion matrix, which consists of four parts: True Positive (TP): the number of positive samples predicted correctly, True Negative (TN): the number of negative samples predicted correctly, False Positive (FP): the number of negative samples predicted as positive (Type I error), and False Negative (FN): the number of positive samples predicted as negative (Type II error).

The definition of Sensitivity is as equation 5.4, it can be seen that Sensitivity shows the ability of the model to identify positive sample points.

$$\text{Sensitivity} = \frac{\text{TP}}{\text{TP}+\text{FN}} \tag{5.4}$$

While Specificity gives the ability of the model to identify negative sample points, which calculated by formula 5.5

$$\text{Specificity} = \frac{\text{TN}}{\text{TP}+\text{FP}} \tag{5.5}$$

Precision represents the proportion of true positive samples among the positive samples predicted by the classifier

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \tag{5.6}$$

Accuracy represents the overall judgment ability of the classifier, that is, the proportion of the total correct predictions including positive and negative instances

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{NP} + \text{TN} + \text{FN}} \tag{5.7}$$

The F1 score takes into account both the Precision and Sensitivity of a classification model, and is a more comprehensive metric for evaluating model performance, which can be calculated as 5.8

$$F_1 = 2 \cdot \frac{\text{Precision} \cdot \text{Sensitivity}}{\text{Precision} + \text{Sensitivity}} \tag{5.8}$$

Finally, the Matthews correlation coefficient (MCC) is used in machine learning to measure binary and multiclass classification performance. It takes into account true and false positives and negatives, and is generally considered a more complex and balanced measure of performance, it is calculated by 5.9

$$MCC = \frac{\text{TP} \times \text{TN} - \text{FP} \times \text{FN}}{\sqrt{(\text{TP} + \text{FP})(\text{TP} + \text{FN})(\text{TN} + \text{FP})(\text{TN} + \text{FN})}} \tag{5.9}$$

The performance of these nine models on the mobile dataset and beauty dataset are shown in Table 5-5 (a) and (b), respectively.

Table 5-5 The Performance of the Model Based on Different Dataset

(a) The Performance of the Model Based on Mobile Dataset

Method	TP	FN	FP	TN	Sensitivity	Specificity	Precision	Accuracy	F1	MCC
Naive Bayes	38	496	16	945	0.07	0.98	0.70	0.65	0.13	0.14
KNN	255	279	197	764	0.48	0.8	0.56	0.68	0.52	0.28
Random Forest	370	164	162	799	0.69	0.83	0.7	0.78	0.69	0.52
SVM	284	250	164	797	0.53	0.83	0.63	0.72	0.58	0.38
CART	328	206	149	812	0.61	0.85	0.69	0.76	0.65	0.47
Bagged CART	358	176	171	790	0.67	0.82	0.68	0.77	0.67	0.49
XGB	360	174	142	819	0.67	0.85	0.72	0.79	0.7	0.53
Boosted Tree	351	183	135	826	0.66	0.86	0.72	0.79	0.69	0.53
Bagged AdaBoost	328	206	163	798	0.61	0.83	0.67	0.75	0.64	0.45

(b) The Performance of the Model Based on Beauty Product Dataset

Method	TP	FN	FP	TN	Sensitivity	Specificity	Precision	Accuracy	F1	MCC
Naive Bayes	737	4	234	3	0.99	0.01	0.76	0.76	0.86	0.04
KNN	673	68	178	59	0.91	0.25	0.79	0.74	0.85	0.20
Random Forest	741	0	232	5	1	0.02	0.76	0.76	0.86	0.13
SVM	708	33	199	38	0.96	0.16	0.78	0.76	0.86	0.19
CART	741	0	189	48	1	0.20	0.78	0.81	0.89	0.40
Bagged CART	706	35	152	85	0.95	0.36	0.82	0.81	0.88	0.41
XGB	723	18	164	73	0.98	0.31	0.82	0.81	0.89	0.42
Boosted Tree	738	3	202	35	1	0.15	0.79	0.79	0.88	0.32
Bagged AdaBoost	741	0	189	48	1	0.2	0.8	0.81	0.89	0.40

Through the comparative analysis of the performance results of the models, the eXtreme Gradient Boosting classification technique was the one that presented the best results in this particular case study. Therefore, we choose the importance of variables in this model in determining the final classification results to explain the impact of different variables. We use the `varImp()` function in `caret` package to get the importance of each variables, and we can get t the TOP20 important variables of the two models and shown in Figure 5-9.

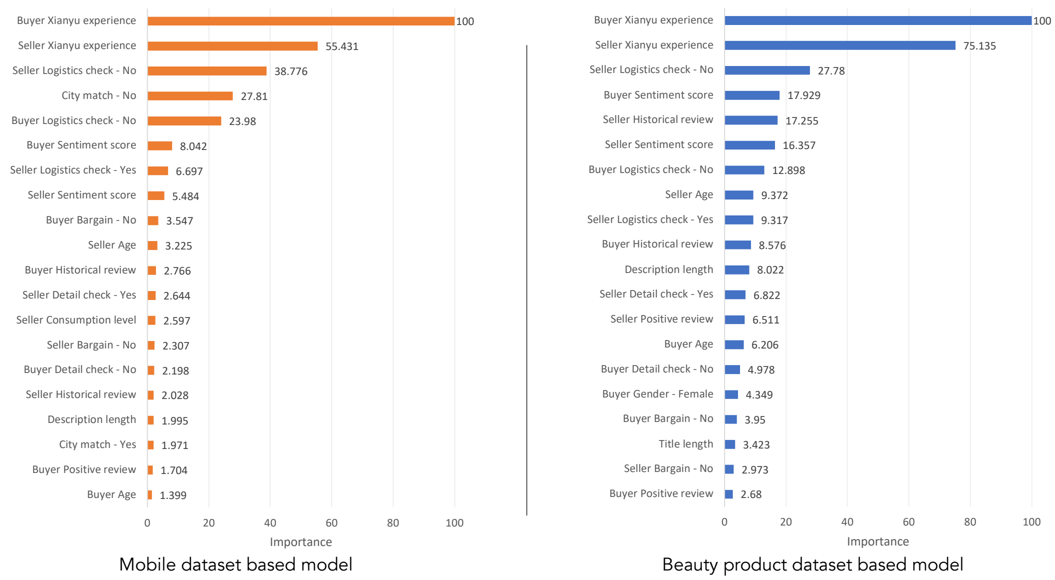


Figure 5-9 The Importance of Variables in Different Classification Models

We can see that in both models, the historical experience of using Xianyu by both the buyer and the seller is the most decisive variable, and user characteristics such as age also have some influence. The features mentioned in the chat information that we focused on in this chapter also have a significant impact on both models, such as user confirmation of logistics information and the emotional state of both the buyer and seller during the chat (it should be noted that we used one-hot encoding to handle categorical variables during data preprocessing, so the presence or absence of categorical variables is considered separately).

In addition, we discovered some interesting phenomena regarding the differences in variable importance between the model based on mobile phone data and the model based on beauty products data. It can be seen that whether the buyer and seller are in the same city is an important attribute in determining transactions for mobile products transaction but not so important for the beauty product. Another phenomenon that can be found is that the buyer's and seller's favorable comments numbers are more important for the transaction of beauty products than mobile phones. Finally, we can observe that the buyer's lack of bargaining is an important attribute in the mobile phone model but not so important in the transaction of beauty products. We can explain the above phenomenon from industry experience. We believe that buyers and sellers are more inclined to trade in the same city for high-priced commodities such as mobile phones, which is a safer way for second-hand product transactions. Beauty products are less standardised than mobile phones, and buyers and sellers need to communicate more about product details. And because phones are usually more expensive, sellers are usually more willing to deal with buyers who are not price sensitive.

5.5 Comparing the sentiment factors contribution to the model

Further, we compare the contribution of emotional factors to the performance of the model by comparing whether the model uses emotional factors. We use the best-performing eXtreme Gradient Boosting technique to model the datasets with/without sentiment factor respectively, and their performance comparison data are shown in Table 5-6 (a) and (b), respectively.

We use eXtreme Gradient Boosting technology to model the data sets with and without emotional factors. By comparing the performance of the models, we can find that after removing the emotional factors, the prediction accuracy of the model will drop more for mobile phones than for beauty product. It shows that emotional factors are more significant in affecting the conversion of mobile phone transactions than beauty products.

Table 5-6 The Performance of the Model Based on Different Dataset

(a) The Performance of the Model Based on Mobile Dataset

Method	TP	FN	FP	TN	Sensitivity	Specificity	Precision	Accuracy	F1	MCC
Include Sentiment	360	174	142	819	0.67	0.85	0.72	0.79	0.7	0.53
Exclude Sentiment	239	295	175	786	0.45	0.82	0.58	0.69	0.5	0.28

(b) The Performance of the Model Based on Beauty Product Dataset

Method	TP	FN	FP	TN	Sensitivity	Specificity	Precision	Accuracy	F1	MCC
Include Sentiment	723	18	164	73	0.98	0.31	0.82	0.81	0.89	0.42
Exclude Sentiment	738	3	189	48	1	0.2	0.8	0.8	0.88	0.38

5.6 Chapter Summary

In this chapter, we analyse the impact of the chat process in the Xianyu second-hand transaction on the final transaction result and build several machine learning models to forecast the final result. During the stage of chat feature extraction and statistical analysis, we mainly focused on studying the emotional state, motivation, and bargaining strategies of both buyers and sellers during their chats. In the prediction phase, we further incorporated multiple variables including user features, product post features, and chat features into the model. The main conclusions include

1) The emotional state of buyers and sellers significantly impacts the final transaction result. A more positive emotional attitude between buyers and sellers can lead to higher conversion rates. Moreover, the emotional states of buyers and sellers are not independent. A positive emotional attitude of one party can make the other party maintain a positive emotional attitude with a high probability and vice versa. The subsequent analysis of variable importance in the classification models further confirms the conclusion that the emotional

state during the chat will significantly impact the transaction outcome.

2) In addition, behaviors like bargaining and confirming product details during the chat process will significantly reduce the final transaction rate. If the buyer and seller start to confirm the logistics information of the goods, the transaction has a higher probability of success. At the same time, confirming the authenticity of the commodity has no significant impact on the final transaction result. Although the subsequent analysis of variable importance in the classification models also confirmed the significant impact of chatting motivation, such as confirming logistics information and bargaining behavior, on transaction results, the impact of bargaining strategies was not very significant. This may be because bargaining strategies are further behaviors built on top of bargaining behavior and thus have limited influence.

3) This research confirms that predictive modeling is effective in the academic field and that decision makers can use these models to effectively match buyers and sellers and improve overall conversion rates through improved communication skills. After comparing the variable importance of models based on different product trading data, we found that the emphasis of buyers and sellers in the transaction process varies for different products. For high-value products, buyers and sellers tend to convert online transactions into offline transactions to reduce the level of risk. For products with lower standardisation, buyers and sellers need to have more patience to communicate product details in order to achieve a higher transaction conversion rate.

Chapter 6 Conclusion

In this study, we conducted comprehensive research on user behaviour in the online second-hand trading platform. The research content mainly involves the three main problems in user behaviour on the online second-hand trading platform

1) **Platform selection problem**: when consumers are planning to buy a particular commodity, will they choose online first-hand shopping platforms like Taobao or online second-hand trading platforms like Xianyu? What factors will impact their decisions?

2) **Purchase intention of second-hand product**: When faced with different second-hand products and second-hand sellers, what factors will drive consumers to show a stronger purchase intention for a certain product?

3) **Transaction result prediction**: Can the strategies used by buyers and sellers in the communication process affect the final transaction results and can this information be used to predict the final results?

As shown in Figure 1-4, these three questions cover the primary behaviour process of users in the online second-hand trading platform. We put forward nine hypotheses for these three questions and verified our hypotheses by analysing real word user data in the Xianyu second-hand trading platform. In Chapter 3, we analysed the issue of platform selection by establishing a logistic regression model which contain product information and user information, determining the influence direction and significance level of different variables. In Chapter 4, we used whether the buyer of second-hand products on Xianyu initiated a chat as an indicator of purchase intention, and validated the significance of the impact of variables such as the historical experience, past evaluation levels, and gender of both the buyer and seller on the purchase intention of second-hand products through statistical tests and logistic regression models. In Chapter 5, we employed machine learning-based natural language processing methods to extract feature variables in the communication process between the buyer and seller and analysed the influence of these variables on the final transaction outcome. We also established multiple machine learning prediction models and predicted the final transaction results using multi-dimensional data.

6.1 Answers to Posed Problems

6.1.1 Platform Selection Problem

For the first question, we analysed the different behaviours of active users on both Xianyu and Taobao when choosing a platform. It focuses on the impact of three variables: user's consumption level, product brand score, and product emotional (functional) value, on consumer behaviour. Data analysis shows that users' consumption level negatively affects their Xianyu purchase probability. At the same time, if the user wants to buy a product with a higher brand score, then the increase in his (her) consumption level will have a more significant negative effect on the probability of selection on the Xianyu platform. This result reject the **Hypothesis 1** given in Chapter 2. For **Hypothesis 2** we find out that, generally speaking, an increase in the product brand score will increase consumers' interest in purchasing these products on Xianyu's second-hand platform. However, when the users are with high consumption levels, the positive impact of the brand score will be weak.

At last, for **Hypothesis 3**, we should reject the hypothesis, consumers prefer to buy products with high emotional value on the Xianyu second-hand platform. At the same time, the emotional (functional) value proportion of the product will moderate the impact of consumption level and product brand score on platform selection. Commodities with a high emotional value will intensify the adverse effect of augmented consumption levels on the purchase rate for the Xianyu platform, whereas those with a high functional value will intensify the positive effect of enhanced brand scores on the purchase rate for the Xianyu platform.

6.1.2 Impact Factors for Second-Hand Product Purchase Intention

In the study of this problem, we choose to regard second-hand goods buyers' initiative to initiate chatting with sellers as an expression of buyers' willingness to purchase. Through data analysis, we found that both the experience of sellers and buyers on the Xianyu platform will affect their willingness to buy a certain product. Overall, products from more experienced sellers are more likely to be favored by buyers due to their higher creditworthiness of them. Although inexperienced sellers have a lower probability of being selected, professional buyers have a higher probability of accepting items sold by amateur sellers than amateur buyers. This is because experienced buyers have a stronger ability to identify risks and can accept higher-risk transactions. This result gives us enough evidence to reject the **Hypothesis 4**, the historical transaction experience information of buyers and sellers in the Xianyu second-hand market jointly affects the final chat conversion. Experienced buyers prefer sellers with higher historical sales, while inexperienced buyers prefer similarly inexperienced sellers. Likewise, we reject the **Hypothesis 5**, our analysis results found that the increase in the seller's positive review rate will usually increase the chat conversion rate, but an excessively high positive review rate will lead to a decline in buyers' willingness to buy. As for **Hypothesis 6**, we find that the impact of gender is significant. The chat conversion rates of female buyers are significantly higher than male buyers, and female buyers will prefer to initiate chats with male sellers. However, the impact of geographic location matching is not significant. Finally, for the **Hypothesis 7**, we find that a shorter and more readable title will significantly increase the final chat conversion rate, but the length of the description of the product post has no significant impact on the chat conversion.

6.1.3 Transaction Conversion Analysis and Prediction

In the research of this part of the question, we mainly use Natural Language Processing (NLP) technology to analyse the content of the chat between buyers and sellers. First, we conducted data analysis and statistical tests on the extracted variables to verify the conjectures raised in the Chapter 2. In order to test **Hypothesis 8**, we obtained the emotional state of buyers and sellers in the chat through the analysis of the use of Emoji and the overall chat content. The data shows that a more positive emotional state between buyers and sellers during the chat process will significantly increase the probability of a successful transaction. Second, we use the BERT method to find out the strategic choices of buyers and sellers in the bargaining process from the chat text. The data analysis results verified **Hypothesis 9**. If buyers and sellers use strategic bargaining methods, such as threatening to withdraw from the transaction, the success rate of the transaction can be significantly increased.

In addition, we propose a model powered by data mining classification techniques that predicts the likelihood of a deal based on the demographic characteristics of buyers and sellers, and the content characteristics they exhibit during communication conversations. We confirm that predictive modeling is effective in the academic field, in practical applications, operators can use big data technology to match more suitable buyers and sellers, thereby increasing the probability of successful online second-hand transactions. In the analysis of variable importance in predictive models, we also found that communication skills such as emotional state and chatting motivation are relatively important for predicting the final transaction outcome. In addition, the importance of variables in prediction varies for different products. For valuable products, the matching of geographical location is crucial, while for products with complex categories, smooth communication and interaction become more important. Furthermore, online second-hand trading platforms such as Xianyu can guide users to use more appropriate communication methods to increase the likelihood of successful transactions, which can also help improve the platform's credibility and vitality.

6.2 Future Work

In this study, we mainly use the method of the statistical model to discuss some problems in the second-hand market. Restricted by the technical level and other data limitations, we simplified many problems during the analysis process. For example, the influence of functional product value. In our research, functional product value is acquired from the knowledge provided by professionals. However, the value estimates of different consumers for the same product are usually different. However, since we cannot obtain the psychological perception of each consumer, we can only use the perception of a small group of professionals in place of the preferences of all. To solve this problem, we can design a new theoretical model to describe and simulate the value perception of each consumer so that more accurate results can be obtained in subsequent research. This also provides an idea for follow-up research.

In addition, limited by the lack of data dimensions, our estimation of consumers' spending power could be clearer and more accurate. For example, consumers on Taobao are more inclined to female users, which may be related to the nature of the platform itself. More male users may spend on something other than the Taobao platform due to higher consumption levels, which may lead to our underestimation of their consumption levels. In addition, due to the nature of the platform, many consumers may choose other platforms, such as JD.com, for shopping when purchasing many high-priced electronic products, so the historical purchase amount cannot accurately reflect the purchasing power of consumers. Therefore, more accurate results may be obtained if the consumer's spending power can be estimated from more dimensions, such as education level, job nature, and other aspects.

Finally, there are many other problems in the transaction process of the second-hand platform, such as the buying and selling of speculators and online fraud et al. These aspects are not discussed in this paper, but these issues can serve as a starting point for more detailed research in the future.

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