THE INFLUENCE OF SOCIAL COMMERCE ON CHINESE CONSUMER PURCHASE BEHAVIOUR: CASE STUDY FROM GUANGDONG PROVINCE

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MASTER OF SCIENCE
IN DIGITAL INNOVATION AND FINANCIAL TECHNOLOGY

GRADUATE SCHOOL
CHIANG MAI UNIVERSITY
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A THESIS SUBMITTED TO CHIANG MAI UNIVERSITY IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE DEGREE OF MASTER OF SCIENCE IN DIGITAL INNOVATION AND FINANCIAL TECHNOLOGY

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Xinke Li

หัวข้อการค้นคว้าอิสระ อิทธิพลของโซเชียลคอมเมิร์ซต่อพฤติกรรมการซื้อของผู้บริโภคชาวจีน: กรณีศึกษาจากมณฑลกวางตุ้ง

ผู้เขียน นางสาว ซินเคอ ลี

ปริญญา วิทยาศาสตรมหาบัณฑิต (นวัตกรรมดิจิทัลและเทคโนโลยีการเงิน)

คณะกรรมการที่ปรึกษา อาจารย์ ดร.เพียงออ เลาหะวิไลย อาจารย์ที่ปรึกษาหลัก
อาจารย์ ดร.นที นาคธนสุกาญจน์ อาจารย์ที่ปรึกษาร่วม

บทคัดย่อ

วัตถุประสงค์:

มีสององค์ประกอบพื้นฐานในการค้าทางสังคม: การค้าและสังคม แม้ว่าจะเป็นปรากฏการณ์ใหม่ในการวิจัยการตลาด แต่องค์ประกอบทางสังคมก็ไม่ค่อยมีใครพูดถึง ดังนั้น จุดประสงค์ของบทความนี้คือเพื่อหารือเกี่ยวกับปัจจัยทางสังคมที่มีอิทธิพลต่อความตั้งใจและพฤติกรรมในการซื้อของผู้บริโภคในบริบทของการค้าทางสังคม

วิธีการ:

การศึกษานี้ดำเนินการในสองส่วน สำหรับแบบสอบถามตัวอย่างที่ถูกต้อง 300 รายการที่ได้รับภายใต้แพลตฟอร์มเครือข่ายสังคม WeChat อันดับแรก เราทำการศึกษาเชิงทฤษฎี เราใช้ทฤษฎีการเรียนรู้ทางสังคมและทฤษฎีการสนับสนุนทางสังคมเพื่อวิเคราะห์ความตั้งใจอีคอมเมิร์ซทางสังคมและพฤติกรรมผู้บริโภคโดยการสร้างแบบจำลองสมการโครงสร้าง (SEM) เพื่อทดสอบสมมติฐานการวิจัยที่เสนอ เราเชื่อว่าการทดลองสามารถเข้าใจได้ในบางกรณี และผลการทดลองสามารถชี้แนะแนวทางปฏิบัติได้ ดังนั้นเราจึงใช้ Pinduoduo ซึ่งเป็นแพลตฟอร์มอีคอมเมิร์ซโซเชียลชั้นนำในประเทศจีนเป็นกรณีศึกษา เราใช้ทฤษฎีเส้นทางพฤติกรรมลูกค้า 5A ของ Philip Kotler เพื่อศึกษาพฤติกรรมอีคอมเมิร์ซทางสังคมของกลุ่มตัวอย่างโดยใช้วิธีการทางสถิติ SPSS

ผลลัพธ์:

ผลจากแบบจำลองทางทฤษฎีแสดงให้เห็นว่าการเรียนรู้ทางสังคมมีผลในเชิงบวกต่อการสนับสนุนทางสังคม ความตั้งใจของอีคอมเมิร์ซในสังคม และพฤติกรรมการซื้อของผู้บริโภค แต่ผล

ของการเรียนรู้ทางสังคมต่อพฤติกรรมการซื้อนั้นเป็นทางอ้อมมากกว่าโดยตรง นอกจากนี้ การสนับสนุนทางสังคมมีผลในเชิงบวกต่อความตั้งใจของอีคอมเมิร์ซทางสังคม และการสนับสนุนทางสังคมและความตั้งใจของอีคอมเมิร์ซทางสังคมมีผลดีต่อพฤติกรรมการซื้อ ผลการวิเคราะห์ทางสถิติกรณีศึกษาแสดงให้เห็นว่าผู้บริโภคค่อนข้างพอใจกับมาตรการทั้งหมดในแบบจำลองโครงสร้าง ซึ่งพิสูจน์ได้ว่าการเรียนรู้ทางสังคมและการสนับสนุนทางสังคมช่วยอำนวยความสะดวกในการปฏิสัมพันธ์ทางสังคมของผู้บริโภค ความตั้งใจของอีคอมเมิร์ซในสังคม และพฤติกรรมการซื้อจริง

คำแนะนำ:

งานวิจัยนี้ได้นำไปสู่การเปลี่ยนแปลงในการวิจัยเกี่ยวกับอีคอมเมิร์ซทางสังคมไปสู่ด้านสังคมมากกว่าด้านอีคอมเมิร์ซ แบบจำลองทางทฤษฎีที่เรานำเสนอจะขับเคลื่อนการพัฒนาการวิจัยเพิ่มเติมเกี่ยวกับพฤติกรรมการซื้อของผู้บริโภค นอกจากนี้ เรายังแสดงโปรไฟล์ผู้บริโภค ซึ่งเราเชื่อว่าสามารถช่วยแนะนำการปรับปรุงรูปแบบธุรกิจ การตลาดผลิตภัณฑ์ และกลยุทธ์ทางธุรกิจสำหรับแพลตฟอร์มอีคอมเมิร์ซโซเชียล ที่สำคัญกว่านั้นคือส่งเสริมการพัฒนาอุตสาหกรรมการค้าเพื่อสังคม

Thesis Title The Influence of Social Commerce on Chinese Consumer Purchase Behavior: Case Study from Guangdong Province

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ABSTRACT

Objectives:

There are two basic components to social commerce: commercial and social. Although a relatively new phenomenon in marketing research, social component is rarely discussed. Therefore, the purpose of the paper is to discuss the social factors that influence the consumers' purchase intentions and behaviors in the context of social commerce.

Methods:

This study is conducted in two parts. For the 300 valid sample questionnaires obtained under the WeChat social networking platform, we first conduct a theoretical study. We used social learning theory and social support theory to analyze social e-commerce intentions and consumer behavior by constructing structural equation modeling (SEM) to test the proposed research hypotheses. We believe that experiments can be understood in specific cases and experimental results can guide practice, so we use Pinduoduo, a leading social e-commerce platform in China, as a case study. We applied Philip Kotler's 5A Customer Behavior Path theory to study the social e-commerce behavior of the sample through SPSS statistical methods.

Results:

The theoretical model results show that social learning has a positive effect on social support, social e-commerce intention and consumer purchase behavior, but the effect of social learning on purchase behavior is indirect rather than direct. Also social support has a positive effect on social e-commerce intention, and social support and social e-commerce intention have a positive effect on purchase behavior. The case study statistical analysis results show that consumers are relatively satisfied with all the measures in the structural model, proving that social learning and social support do facilitate consumers' social interactions, social e-commerce intentions and actual purchase behaviors.

Recommendations:

This research has led to a shift in research on social e-commerce to the social aspect rather than the e-commerce aspect. The theoretical model we propose will drive further development of research on consumer purchase behavior. In addition, we output a consumer profile, which we believe can help guide the improvement of business models, product marketing, and business strategies for social e-commerce platforms. More important, it promotes the development of social commerce industry.

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LIST OF ABBREVIATIONS

S-commerce	Social commerce
SL	Social learning
SS	Social support
SCI	Social commerce intention
PB	Purchase behavior
LFC	Learning from forums and communities
LRR	Learning from ratings and reviews
LSR	Learning from social recommendations
IS	Informational support
ES	Emotional support
TS	Tangible support
PDD	Pinduoduo

CHAPTER 1

INTRODUCTION

1.1 Historical background

China's economy has recently acquired a new pattern of domestic and international double-cycle development with the booming development of the e-commerce industry, which has helped to release the demand for e-commerce in the rural market, and close the geographical consumption gap in the rural market. By the end of 2020, China's digital economy jumped to second place in the world, reaching 39.2 trillion yuan, according to the China Internet Development Report (2021) [1]. The 48th Statistical Report on the Development of China's Internet [2] shows that, as of June 2021, China had 1.011 billion Internet users, 812 million of whom were online shoppers, or 80.3% of the total number of users. By 2020, China's e-commerce transactions will total 37.21 trillion yuan, including 27.95 trillion yuan in commodity e-commerce and 8.08 trillion yuan in service e-commerce. The transaction scale of social e-commerce industry reaches 2532.35 billion yuan in 2021. Among them, in terms of growth rate, the growth rate was as high as 98.19% in 2016 and 71.71% year-on-year in 2019, and the growth rate dropped sharply to 11.62% in 2020 due to the impact of the epidemic. Due to the normalization of the epidemic, the growth rate in 2021 is 10.09%, showing a further decline. However, China's e-commerce industry is maturing, with online sales channels becoming an important venue for Chinese consumers to make purchases. With the accelerated development of social retailing, online retail sales in China will grow even faster.

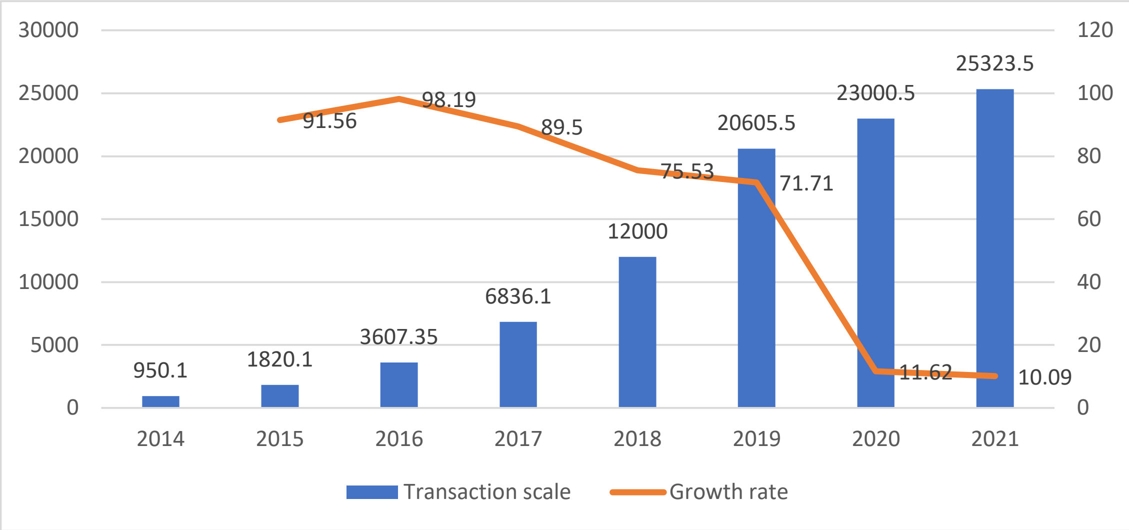

Figure 1.1 Transaction scale and growth rate of social commerce industry [3]

As the number of users on the Internet grows, the number of market transactions increases, and business efficiency increases exponentially. 5G will integrate various new information technologies deeply with the real economy and enhance industrial upgrading as it continues to be applied on the ground [1].

1.2 Literature review

The booming e-commerce industry has prompted scholars to conduct a large number of research studies, among which understanding social factors influence online shopping behavior is a long-standing research question [4]. Most studies have concentrated on the "shopping" aspects of the phenomenon and largely ignored its "social" aspects. Social commerce is considered an important extension of traditional e-commerce, but empirical studies in this area remain limited [5]. Social media platforms in the context of social shopping are not just places to chat and share, but they also serve as a platform for communication between brands and customers, making social media platforms an important channel for increasing the willingness of customers to purchase products and services, and increasing the likelihood that they will participate in online social activities.

1.3 Objectives

An individual's purchasing decision is influenced by a number of factors. Every day, consumers make many purchasing decisions since each of us plays the role of a consumer. Additionally, understanding this topic assists marketers in targeting customers more efficiently, improving their products and services, increasing customer satisfaction, creating a competitive advantage, and enhancing company value. Yet most online consumer behavior studies have been carried out in developed countries, while developing countries have rarely been studied [17]. As part of this study, a theoretical model based on social learning (learning from forums and communities, learning from ratings and reviews, and learning from recommendations) and social support (emotional support, informational support, and tangible support) will be developed and used to examine consumer purchasing behavior on social commerce platforms, especially the factors that influence consumer decision making process, with the goal of assisting consumers in making informed purchasing decisions.

These questions are included in the research:

(1) To study factors that influence consumers' purchase intentions and behaviors, in the context of social commerce.

(2) To study how these factors affect consumers' purchase intentions and purchase behaviors when it comes to social commerce.

Our study aims to identify the factors that influence consumers' social commerce intentions and purchase behaviors by investigating the role and influence of social learning and social support on social willingness to shop and share. This third section presents the hypotheses and model for the study. Section four describes the implementation and results of the study. Section five focus on social commerce platforms in China and analyze one well-known platform (Pinduoduo) in particular. Lastly, the conclusions, implications, and limitations are presented.

1.4 Methodology

This study is conducted in two parts. For the 300 valid sample questionnaires obtained under the WeChat social networking platform, we first conduct a theoretical study. We used social learning theory and social support theory to analyze social e-commerce intentions and consumer behavior by constructing structural equation modeling (SEM) to test the proposed research hypotheses. We believe that experiments can be understood in specific cases and experimental results can guide practice, so we use Pinduoduo, a leading social e-commerce platform in China, as a case study. We applied Philip Kotler's 5A Customer Behavior Path theory to study the social e-commerce behavior of the sample through SPSS statistical methods.

1.5 Advantage of the study

This research has led to a shift in research on social e-commerce to the social aspect rather than the e-commerce aspect. The theoretical model we propose will drive further development of research on consumer purchase behavior. In addition, we output a consumer profile, which we believe can help guide the improvement of business models, product marketing, and business strategies for social e-commerce platforms. More important, it promotes the development of social commerce industry.

1.6 Scope of the study

This article investigates the factors influencing consumer purchasing behavior and the relationship between them, and we will conduct a questionnaire survey on Chinese consumers' online purchasing behavior on social e-commerce platforms, focusing on Guangdong Province, China. We believe that Guangdong province, with its developed economy, high spending power of residents, and strong purchasing power on social commerce platforms, is typical for the study of user behavior on social commerce platforms in China, and therefore suitable for this study.

CHAPTER 2

LITERATURE REVIEW

2.1 Social commerce

In 2005, social commerce was introduced, and is often seen as a subset of e-commerce. "Social commerce" is defined by [7] as social interaction among network members and exchange-related activities, including all steps of the decision-making process for consumers. Web 2.0 features and social media are used in social commerce, which is a new form of e-commerce. There are two components to social commerce, the commercial component and the social component. At present, it is implemented in two ways, one by integrating social features into traditional e-commerce sites and the other by integrating commercial features into social sites. The addition of social functions to e-commerce websites to encourage interaction and sharing and the addition of shopping functions to social networks will jointly contribute to the formation of social commerce [8].

Social commerce is a development of e-commerce. Customers use social platforms to learn about products before purchasing them, chat with vendors, and share their experience after purchasing them. An e-commerce transaction is considered social once social elements are applied, such as following, sharing, communicating, discussing, and interacting. Merchants are not the only ones to initiate social commerce interaction and promotion. Consumers also play a major role in social commerce promotion by sharing recommended products with their social network contacts. Social media are used to create social commerce and to support individual purchasing decisions by various Internet-based business applications that support social interactions. E-commerce giants have made social commerce one of their main strategies for future growth due to this interaction, the need for e-commerce to form social commerce, as well as the sustainability of social commerce [9].

Figure 2.1 A triad relational model of social commerce [10]

Though social commerce is often referred to as a combination of social media and e-commerce, it emphasizes social media-based commerce activities and embraces all key features of social networks. Compared to traditional e-commerce, it has several benefits. As one example of traditional e-commerce, consumers search for products, add products to shopping carts, consult strangers or use preference-based systems to make purchases. But in a social commerce environment, consumers consult their friends for advice and suggestions, freely share experiences with products and services, and shift from inefficient individual consumer decision making to collaborative sharing and social shopping [5]. As a result, it promotes social and collaborative interactions among consumers, allows the sharing and discussion of purchases, and creates great potential for creating new social relationships and sustaining existing ones, resulting in greater conversion rates [11]. In addition, consumers tend to imitate the purchases their friends make or to purchase products that are similar to their friends' purchases [4].

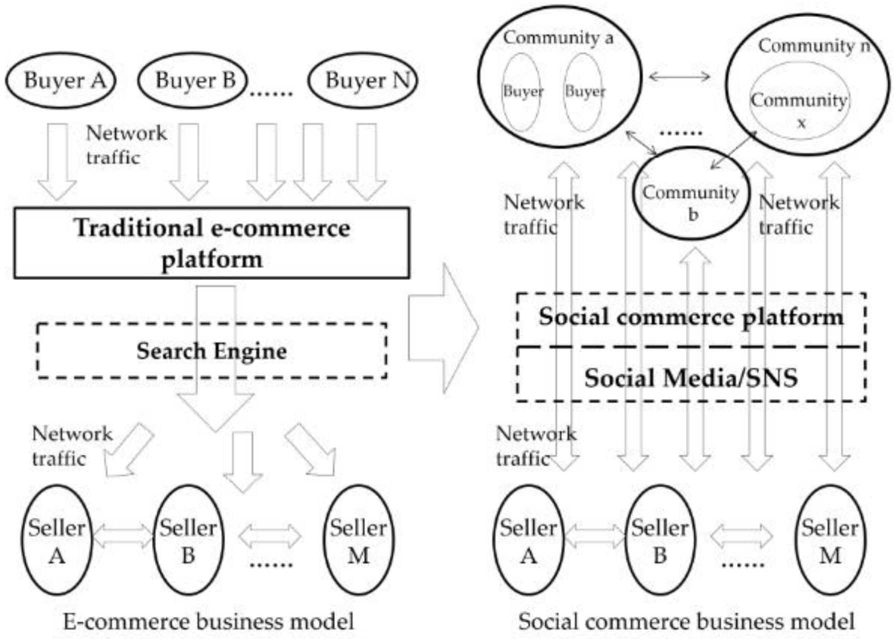

Figure 2.2 The transformation from e-commerce to social commerce [12]

There are five key characteristics of social commerce: interactivity, stickiness, personalization, socialization, and customer-to-customer interaction. With the help of social commerce features, customers can interact with a large number of other buyers, which enhances their online shopping experience and enables them to make more informed decisions. The two main outcomes of social commerce are improved purchase decisions and an overall sense of pleasure. In order to make more informed and accurate purchasing decisions, consumers should participate in the exchange of product-related information. When consumers interact with one another using social commerce features, they also experience pleasure. These two outcomes enhance the customer's shopping experience, entertain, reduce shopping costs, and provide real-time marketing within a traditional e-commerce setting [13].

Social interaction can be achieved through shopping. An environment dominated by products becomes an environment dominated by users with social shopping. We adopt the definition of social commerce from [7] and emphasize further the "social" nature of social commerce in our study.

2.2 Social commerce intention

Researchers use intentions as a measure of likely human behavior, and intentions have been shown to be a significant predictor of behavior as they have a direct correlation to actual behavior. A person's intent to conduct business on the site is measured by their social commerce intention [14]. A social business intent precedes a social commerce action. As a result, social commerce occurs. In order to understand consumer behavior in social commerce, we use social commerce intention [9].

2.3 Social Learning Theory (SLT)

Bandura's social learning theory is widely used in social and behavioral sciences to address a wide range of issues and has seldom been applied to online purchasing behavior [16]. It investigates the ways in which an individual's socialization process is influenced by social influences and how self-learning occurs through social influences. Observing and modeling other people's behavior is the basis of social learning. The individual replaces the observed behavior with the actual behavior after they perceive reinforcement as positive [17].

Taking advantage of others' knowledge and experiences is the essence of social psychology [18]. A social learning process occurs when consumers acquire information and social knowledge about products through social media platforms, including their interaction with the external business structures of social commerce and their internal psychological processes that arise from their experiences [19]. These social commerce platforms enable consumers to gain insight from others' experiences in forums and communities, get valuable information from reviews and ratings posted by others, and also receive advice regarding social advertising. Through this process of learning, consumers acquire enough knowledge to determine whether a product seller is providing accurate information about the product and to determine whether the product will meet their needs. Learning behaviors, in turn, influence their attitudes toward the product and website. Therefore, they are more likely to purchase the product. When learners engage in these behaviors more often, for a longer period of time, and with better quality learning material they will achieve better learning outcomes. In other words, frequency, duration, and quality of materials determine individual learning outcomes [16].

2.4 Social Support Theory (SST)

Social support can be seen as a function of social relationships and explains how their influence on behavior, cognition, and emotions [21]. Psychology and sociology both study social support as a psychological concept. According to [22], it is the social resources that are offered both informally and informally as part of support groups. Members of a community often feel that they are supported physically or psychologically by others.

Due to social media's rapid development, online social networks have become an important source of social support [5]. Support from social networks is one factor involved in business research, as it is one of the key social factors. Social support is considered as an important indicator of customer engagement and positive behavior in social business environments, and is used as a prerequisite in many studies [23]. Having more social support leads to more effective business intentions and influences customers' social behaviors such as sharing helpful information and advice with others [24]. Through social interactions and information, social networks promote social support. Users' willingness to use social platforms and engage in social commerce in the future will also be positively influenced by this supportive climate [25].

The concept of social support is often viewed as multidimensional. [26] argue that it includes two dimensions: information and emotional support, while [27] contend it should also include a third: tangible support. In this paper, we will consider all three dimensions.

1) Informational support (IS)

The purpose of information support is to provide information, advice, knowledge, or assistance to others in a virtual network to help them solve problems or come up with new ideas. Those activities are considered to be practical [28].

2) Emotional support (ES)

A person can provide emotional support by providing information, caring, understanding, or empathy that involves emotional issues and makes the recipient feel valued [21]. This type of support emphasizes the emotional aspect of social support more than information support, contributes to the individual's feeling of belonging and love, and enables the individual to open up and ask for help from other members. When users perceive compassion or care, they receive emotional support [27].

3) Tangible support (TS)

Tangible support is defined as providing goods and services directly to individuals (e.g., using social media business features). An important component of social business is tangible support [27], which promotes the sharing and recommending of information and increases interaction between members. It is the main means of support for social enterprises, along with information and emotional support.

2.5 Purchase intention

An important indicator of customer purchase behavior is customer purchase intention, which is derived from perception of a product or service. A social commerce platform exposes customers to various social commerce features, for example, the ability to rate, review, and recommend products, which encourages them to interact with one another and triggers their purchase intentions.

2.6 Consumer behaviors

Consumer behavior research has become an important topic in marketing and academia in the past few years, and consumer decision processes are one of the major components of consumer behavior research. An innovative approach to building consumer-to-consumer communications is social commerce. Using social media as a platform, consumers contribute product-related information and a variety of personal shopping experiences, which translates into a variety of lucrative business opportunities.

Consumer behavior is the act of choosing, buying, using, or disposing of products, services, and experiences to fulfill needs and wants. It also includes the emotional, behavioral, and psychological reactions of consumers before or after these activities. It seeks to learn about the decision making process of buyers, analyze the characteristics of individuals and groups, and understand people's needs and desires. Additionally, the characteristics of consumers are influenced by factors such as age, income, education, tastes, and other factors. Culture, social, personal, and psychological factors influence consumers' behavior when making purchase decisions, which are largely responsible for different types of behavioral descriptions of consumers [30].

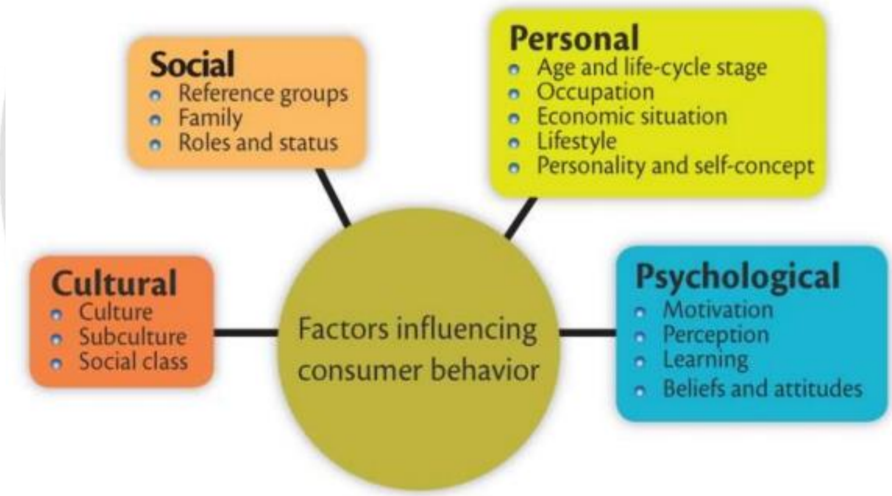

Figure 2.3 Factors influencing consumer behavior

2.7 Type of Buying Behaviors

Depending on the involvement of the purchaser, there are four types of consumer buying behavior when purchasing any product [31].

1) Complex Buying Behavior: When there is a significant difference between two brands and the consumer is highly involved in the buying process, it is called a complex buying behavior.

2) Variety Seeking Behavior: In this case, consumers are not involved much during the purchase process, but there are significant differences between brands.

3) Dissonance Buying Behavior: Here, the consumer is highly involved in the purchase but brands do not differ much.

4) Habitual Buying Behavior: Consumer involvement is low in this case and there are few differences between brands.

Figure 2.4 Four types of buying decision behavior [31]

2.8 5A customers path

Philipp Kotler, Hermawan Kartajaya, and Iwan Setiawan of Mark Plus, Inc. developed the new customer path concept, previously known as Concept 4A. An additional idea is added to this concept, namely advocate, which is referred to as "Concept 5A" that consists of: aware, appeal, ask, act, and advocate [33]. Consumers and others interact in two-way communications more often under the 5A path, which breaks the individual decision-making behavior model of the 4A consumption path. Because of the social media-enabled social element, consumers are not only receiving information, but also sending it out, which is why consumers are not only facing their close partners, but are also facing a larger group of consumers.

Figure 2.5 The 5A customer path in marketing 4.0 [34]

	AWARE	APPEAL	ASK	ACT	ADVOCATE
Customer Behavior	Customers passively receive Long lists of brands from past experiences, marketing possibilities, and/or other people's advocacy	Customers process the messages they receive—creating short-term memory or reinforcing long-term memory—and become interested in only a few short lists of brands.	Driven by their curiosity, customers actively seek more information from friends and family, the media, and/or directly from brands.	Reinforced by more information, Customers decide to buy a particular brand and interact more deeply through the buying, using and/or service process	Over time, customers develop a strong loyalty to the brand, which is reflected in retention, repurchasing, and ultimately advocating for others.
Customer Touch Points	• Knowing a brand's advertisement by accident • Remembering past experiences	• Become interested in the brand • Make a series of brand considerations	• Search for product reviews online • Contact seller • Compare prices	• Buy products • Using the product • Get service	• Product review • Testimonials • Product recommendation to others

Figure 2.6 The indicators framework in marketing 4.0 [35]

As part of Marketing 4.0, merchants have found ways to make their products easier to sell, one of which is via online media or e-commerce. Marketing campaigns and market research using digital media are conducted through online and digital channels such as social networks. Interconnectedness and social adaptability that exist in the Marketing 4.0 era are affecting all parties more strongly, making customers more interested in the opinions of others, as well as sharing their own views and collecting a great many comments, which has undoubtedly contributed to the development of the Internet, particularly social media and e-commerce [35].

CHAPTER 3

RESEARCH DESIGN AND METHODS

3.1 Conceptual Framework

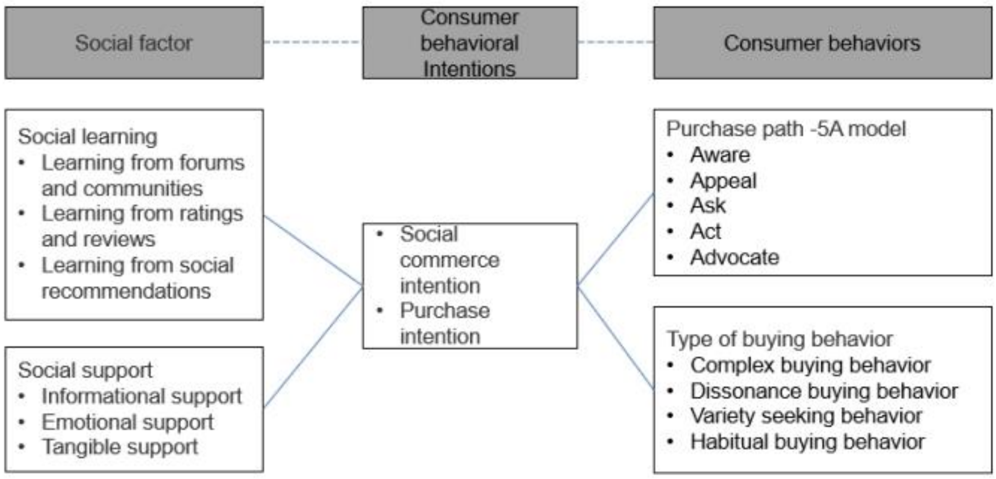

Figure 3.1 Conceptual framework

The purpose of this study is to examine the effects of social learning and social support on consumers' social commerce intentions and purchase behavior, as well as their social shopping and social sharing behaviors.

3.2 Methodology

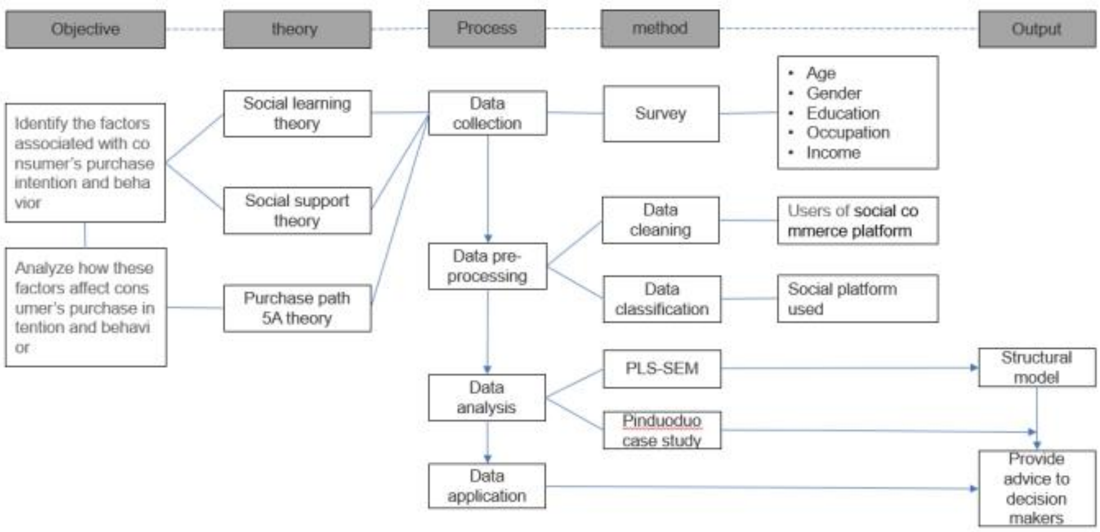

Figure 3.2 Methodology

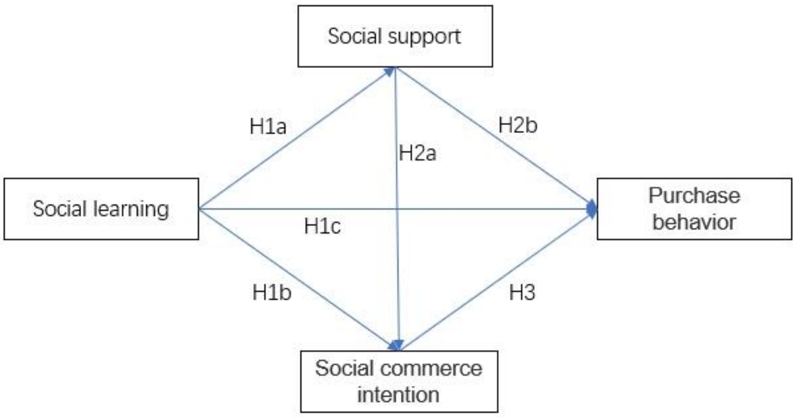

Figure 3.3 Theoretical model

Table 3.1 Construct definitions

Construct	Definition
Social learning	Reflects the social learning aspects of shopping on the s-commerce platform (including learning from forums and communities, learning from ratings and reviews etc.)
Social support	Reflects the social support aspects of shopping on the s-commerce platform (including informational support, emotional support, tangible support etc.)
Social commerce intention	Reflects consumers' social activities on the s-commerce platform (including social sharing, social recommendation etc.)
Purchase behavior	Reflects consumers' purchase activities on the s-commerce platform (including pre-purchase, purchase transactions, post-purchase etc.)

Table 3.2 Research hypotheses

Independent variable	Dependent variable	Research hypotheses
Social learning	Social support	H1a: Social learning is positively associated with social support.

Independent variable	Dependent variable	Research hypotheses
Social learning	Social commerce intention	H1b: Social learning is positively associated with social commerce intention.
Social learning	Purchase Behavior	H1c: Social learning is positively associated with purchase behavior.

Table 3.2 Research hypotheses (continued)

Independent variable	Dependent variable	Research hypotheses
Social support	Social commerce intention	H2a: Social support is positively associated with social commerce intention.
Social support	Purchase Behavior	H2b: Social support is positively associated with purchase behavior.
Social commerce intention	Purchase Behavior	H3: social commerce intention is positively associated with purchase behavior.

3.3 Questionnaire

To validate the proposed theoretical model, quantitative data will be collected through an online questionnaire. The questionnaire measures will be based on a seven-point Likert scale ranging from "totally disagree" to "completely agree". Using a questionnaire platform (https://www.wjx.cn), a questionnaire will be created and distributed via WeChat. Only Guangdong Province, China, will offer the questionnaire, which costs 1 RMB each. We distributed 305 surveys and received 305 responses (100%). (See Chinese version survey at the link: https://www.wjx.cn/vm/w7i0KF0.aspx)

The software used SPSS version 28 to implement the process of frequency analysis of demographic variables.

Table 3.3 Demographic characteristics of respondents

Variable	Category	Frequency	Percentage (%)	Mean value	Standard deviation
Gender	Male	146	49		

Variable	Category	Frequency	Percentage (%)	Mean value	Standard deviation
	Female	154	51	1.51	0.50
Age	Below 18	42	14	3.26	1.48
	18-25	59	20		
	26-30	71	24		
	31-35	57	19		
	36-40	50	17		
	Above 40	21	7		

Table 3.3 Demographic characteristics of respondents (continued)

Variable	Category	Frequency	Percentage (%)	Mean value	Standard deviation
Education Level	High school and below	88	29	2.11	0.87
	Vocational diploma	100	33		
	Bachelor	102	34		
	Master and above	10	3		
Occupation	Civil servants/public institution personnel	24	8	3.22	1.30
	Enterprise staff	92	31		
	Self-employed person	41	14		
	freelancer	81	27		
	Student	62	21		
	Others	0	0		
Income	Below 5000	134	45	1.84	0.93
	5001-10000	99	33		
	10001-15000	50	17		
	15001-20000	14	5		

Variable	Category	Frequency	Percentage (%)	Mean value	Standard deviation
	Above 20000	3	1		
	Total	300	100		

On the basis of the above statistical results, we can illustrate the numerical characteristics of the demographic variables, which reflect the distribution of respondents in this study, where the mean represents the concentration trend, and the standard deviation indicates the fluctuations. The frequency analysis of each variable confirms that the distribution basically meets the requirements of the sample survey. It can be seen that the results of this survey are able to reflect the purchase intention and behaviors of different genders without bias, for example, 49% of males and 51% of females are part of the gender survey.

3.4 Measurements

Table 3.4 Measurements

Variable	Indicator	Item	Source
Social learning (SL)	SL1		
	SL2	3	[36]
	SL3		
Social support (SS)	SS1		
	SS2		
	SS3		
	SS4	6	[9] [14] [37]
	SS5		
	SS6		
Social commerce intention (SCI)	SCI1		
	SCI2		
	SCI3	5	[9] [14]
	SCI4		
	SCI5		

Variable	Indicator	Item	Source
Purchase behavior (PB)	PB1 PB2 PB3	3	[38]

The structural model in this paper consists of four parts, namely, social learning, social support, social commerce intention and consumer purchase behavior. All measurements were adapted from existing classical theoretical literature to suit our research context. The sample collection was conducted in two stages. The first sample of 50 was collected and the selected measures were pretested in the constructed theoretical model to verify the applicability of the measures in the classical model. After removing some of the inapplicable measures, we collected a second sample of 17 retained measures. We need to perform validation factor analysis (CFA) on all the measures. A validation factor analysis (CFA) can be used for studies relating to convergent validity, discriminant validity, as well as common method variance (CMV). In this analysis, the sample size is 300, which is 10 times more than the number of items analyzed, and is considered a medium sample size.

Table 3.5 Specific analysis items

Variable	Indicators	Questions
SL	SL1	The forums and communities provided me with the information i needed for my last shopping experience.
	SL2	The ratings and reviews provided me with the information i needed for my last shopping experience.
	SL3	The social recommendations provided me with the information i needed for my last shopping experience.
SS	SS1	When I encountered a problem, some people on the s-commerce platform would give me information to help me overcome the problem.
	SS2	When faced with difficulties, some people on the s-commerce platform would help me discover the cause and provide me with suggestions.

Variable	Indicators	Questions
	SS3	When faced with difficulties, some people on the s-commerce platform comforted and encouraged me.
	SS4	When faced with difficulties, some people on the s-commerce platform listened to me talk about my private feelings.
	SS5	When faced with difficulties, some people on the s-commerce platform expressed interest and concern in my well-being.
	SS6	When faced with difficulties, some people on the s-commerce platform helped me to solve the problem.
SCI	SCI1	I am willing to provide my experiences and suggestions when my friends on the s-commerce platform want my advice on buying something.
	SCI2	I am willing to share my own shopping experience with my friends on the s-commerce platform.
	SCI3	I am willing to consider the shopping experiences of my friends on the s-commerce platform when I want to shop.
	SCI4	I am willing to ask my friends on the s-commerce platform to provide me with their suggestions before I go shopping.
	SCI5	I am willing to buy the products recommended by my friends on the s-commerce platform.
PB	PB1	I will use the s-commerce platform to find the products I like.
	PB2	I will buy the products or services on the s-commerce platform.
	PB3	I will recommend a product that is worth buying to my friends on the s-commerce platform.

3.5 Data analysis

For the pass-through analysis and factor analysis, structural equation modeling (SEM) was used, while partial least squares (PLS-SEM) was used to test the hypotheses.

To understand the reliability, correlations, and strengths of the study constructs, we used SEM assessment since it offers good reliability and validity and can be used to test measurements, regression analysis, and component factor analysis [39] [40]. It can be used to estimate direct and indirect effects between variables in theoretical models and is one of the most powerful research methods currently available. In the context of our research model and objectives, SEM offers some advantages over other analytical techniques (e.g., multiple linear regression) because it allows us to examine the causal paths proposed between structures. To determine which method to use, we took into account existing methodological literature, our data characteristics, and the study's objectives. PLS-SEM can be used to analyze data even when the sample is not normally distributed. In exploratory studies that focus on testing theoretical models, PLS-SEM is primarily used to develop theories for describing the dependent variables. Hair et al. argue that PLS-SEM is a good choice when a study is aimed at predicting or identifying key drivers. A high level of accuracy can be achieved by identifying features in shopping behavior. Further, it is a component-based method with minimal sample size and residual distribution requirements. Due to the non-normal distribution of the data, this study uses the PLS-SEM method and conducts two steps of SEM analysis using the SmartPLS tool: measurement model and structural model evaluation. Anderson and Gerbing [41] recommended a two-step process for building a valid and reliable measurement model and then testing the structural model. Measurement models test the relationship between potential conformations and indicators, while structural models estimate pathways between exogenous (independent) and endogenous (dependent) potential conformations.

PLS-SEM algorithm:

In the data analysis using PLS-SEM method, we will use three algorithms, namely PLS algorithm, Bootstrapping algorithm, and Blindfolding algorithm.

1. PLS algorithm

PLS algorithm includes the evaluation of reliability, convergent validity, and discriminant validity, which aims to check the quality of the structural model. The computational results will be interpreted using metrics such as path coefficient and interpretable force (R-square).

The basic PLS-SEM algorithm is divided into two steps, firstly the score of the potential configuration is calculated, then the final estimates of the external weights and loads and the path coefficient of the structural model are calculated. The path modeling process is referred to as partial differential modeling since the iterative PLS-SEM algorithm estimates the coefficients of the partial ordinary least squares regression models in the measurement and structural models. The iterative process of the PLS-SEM algorithm estimates all partial regression models, and when calculating the structural model relationships, each endogenous latent configuration represents the dependent variable and its latent antecedent variable is used as the independent variable in the partial regression model. SmartPLS software can provide a graphical user interface to create the model and implement the basic PLS algorithm for model estimation.

2. Bootstrapping algorithm

Bootstrapping algorithm aims to check the relationship between the constructs. The computational results will be interpreted using metrics such as t-statistics.

The bootstrap sample enables the estimated coefficients in PLS-SEM to be tested for their significance. Paths that are nonsignificant or show signs contrary to the hypothesized direction do not support a prior hypothesis, whereas significant paths showing the hypothesized direction empirically support the proposed causal relationship. The procedure creates a large, prespecified number of bootstrap samples by randomly drawing cases with replacement from the original sample. The PLS algorithm estimates the SEM results from each bootstrap sample. Using repeated bootstrap parameter estimation to create an empirical sampling distribution for each model parameter and using the standard deviation of the empirical sampling distribution as the empirical standard deviation of the parameter, the obtained path model coefficients form a self-help distribution, which can be considered as an approximation of the sampling distribution. The PLS-SEM results for all bootstrap samples provide the standard error of each path model coefficient. With this information, t-tests can be performed to measure the significance of the path model relationships. Bootstrap analysis allows statistical testing of the hypothesis that one coefficient is equal to zero (null hypothesis) against another hypothesis that the coefficient is not equal to zero (two-tailed test).

3. Blindfolding algorithm

Blindfolding algorithm aims to check whether the latent variables can be predicted by the indicators. The computational results will be interpreted using metrics such as Q-square.

Blindfolding omits single data points, but not an entire case, imputes the omitted data points (e.g. by using mean value replacement), and estimates the PLS path model. Using these estimates as input, the blindfolding procedure predicts the omitted data points. The R2 value only assesses the explanatory power of the model and does not indicate its out-of-sample predictive power, so the Q2 value is a metric that is often used to assess the quality of the model's predictions. the Q2 value uses a single missing and estimated data point, so the metric is a combination of in-sample and out-of-sample predictions.

CHAPTER 4

RESULTS

SmartPLS version 4 software was used for statistical analysis in this study. Relevant results were obtained using the PLS algorithm. Results are shown in the following paragraphs.

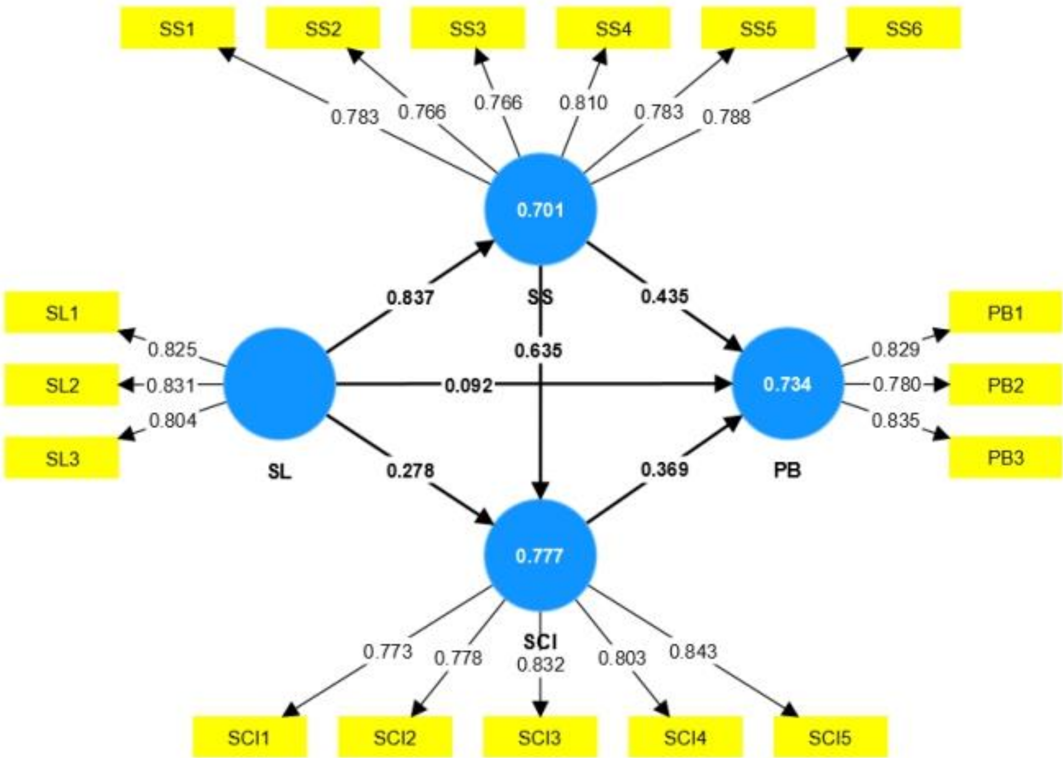

Figure 4.1 Path diagram by PLS algorithm

4.1 Measurement model

Measuring the model's reliability, convergent validity, and discriminant validity requires evaluation.

4.1.1 Reliability Analysis

An analysis of reliability and accuracy of responses to quantitative data (especially attitude scale questions) was conducted. Cronbach's alpha and composite reliability (CR) were used to assess the reliability of the four reflective constructs. AVE (average variance extraction) and CR (composite reliability) were used for convergent validity analysis (convergent validity). High convergence validity is usually indicated by an AVE greater than 0.5 and a CR greater than 0.7. If the Cronbach's alpha value falls between 0.70 and 0.98, the model is considered highly reliable. Over 0.7, the composition reliability (CR) can reach about 0.85, which means the measurement items can support the research framework.

Table 4.1 Construct reliability and validity

	Cronbach's alpha	rho_A	Composite reliability	Average variance extracted (AVE)
PB	0.747	0.751	0.856	0.664
SCI	0.865	0.867	0.903	0.650
SL	0.756	0.757	0.860	0.672
SS	0.873	0.874	0.905	0.612

We compared construct correlations with factor loadings in order to assess discriminant and convergent validity.

4.1.2 Convergent validity

We evaluated the convergence validity using average variance extracted (AVE) and item loading and weight significance. In general, a construct is considered to be valid if its average variation extraction amount exceeds 0.5. And 0.05 was the level of significance for all item loadings. Based on these results, we conclude that our measurement model is adequate in terms of convergent validity.

Table 4.2 Outer loadings

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
PB1 <- PB	**0.829**	0.829	0.019	44.246	0.000
PB2 <- PB	**0.780**	0.779	0.025	31.546	0.000
PB3 <- PB	**0.835**	0.834	0.017	47.744	0.000
SCI1 <- SCI	**0.773**	0.774	0.022	34.844	0.000
SCI2 <- SCI	**0.778**	0.778	0.024	31.861	0.000
SCI3 <- SCI	**0.832**	0.832	0.019	43.519	0.000
SCI4 <- SCI	**0.803**	0.802	0.021	37.386	0.000
SCI5 <- SCI	**0.843**	0.843	0.016	52.099	0.000
SL1 <- SL	**0.825**	0.825	0.017	48.226	0.000
SL2 <- SL	**0.831**	0.830	0.019	44.529	0.000
SL3 <- SL	**0.804**	0.803	0.021	38.277	0.000
SS1 <- SS	**0.783**	0.782	0.024	33.188	0.000
SS2 <- SS	**0.766**	0.765	0.025	30.497	0.000
SS3 <- SS	**0.766**	0.766	0.022	34.859	0.000
SS4 <- SS	**0.810**	0.809	0.019	42.503	0.000
SS5 <- SS	**0.783**	0.783	0.022	36.182	0.000
SS6 <- SS	**0.788**	0.787	0.021	37.737	0.000

Note: □ Indicates regression impact relationship or measurement relationship. All factor loadings (the second column) are significant at $p < 0.05$.

The factor loading value shows the correlation between the factor (latent variable) and the analytic term (significant variable/measure). P<0.05 indicates a correlation at 90% significance level, p<0.01 indicates a correlation at 99% significance level, and p<0.001 indicates a correlation at 99.9% significance level. As can be seen from the above graph, the absolute values of the standardized loadings for all the measures are greater than 0.7

and show significance ($p < 0.001$), implying that each variable is significantly correlated at the 99.9% significance level, and the latent variables have a good measurement relationship with the measures.

Table 4.3 Path coefficients

	PB	SCI	SL	SS
PB				
SCI	0.369			
SL	0.092	0.278		0.837
SS	0.435	0.635		

If the loading of individual factors is greater than 0.5, this mode has internal consistency.

Table 4.4 Collinearity statistics (VIF)

	VIF
PB1	1.549
PB2	1.410
PB3	1.547
SCI1	1.711
SCI2	1.740
SCI3	2.092
SCI4	1.909
SCI5	2.177
SL1	1.527
SL2	1.562
SL3	1.483
SS1	1.858
SS2	1.784
SS3	1.765

	VIF
SS4	2.018
SS5	1.911
SS6	1.881

Based on the VIF<3.3, little multicollinearity exists among these indicators, which is a characteristic of formative constructs. This benchmark was not exceeded by any of the VIF values; therefore, multicollinearity was unlikely to be an issue.

4.1.3 Discriminant validity

Table 4.5 Discriminant validity

	PB	SCI	SL	SS
PB	0.815			
SCI	0.821	0.806		
SL	0.755	0.810	0.820	
SS	0.832	0.868	0.837	0.783

In order to determine the discriminant validity of the scales, we used cross loading. The correlation degree between all measurement items in the same construct is greater than the correlation degree between this construct and another construct, which indicates that the construct has good discrimination validity.

Below you can see that the items for each construct that loaded on each distinct factor were higher than cross-loading on other factors. Therefore, we conclude that all scales have an adequate discriminant validity.

Table 4.6 Cross loadings

	PB	SCI	SL	SS
PB1	**0.829**	0.678	0.633	0.693
PB2	**0.780**	0.623	0.534	0.632

PB3	**0.835**	0.703	0.671	0.706
SCI1	0.631	**0.773**	0.643	0.696
SCI2	0.644	**0.778**	0.605	0.670
SCI3	0.677	**0.832**	0.674	0.725
SCI4	0.653	**0.803**	0.637	0.680
SCI5	0.702	**0.843**	0.704	0.727
SL1	0.642	0.660	**0.825**	0.707
SL2	0.617	0.697	**0.831**	0.692
SL3	0.597	0.634	**0.804**	0.660
SS1	0.662	0.688	0.662	**0.783**
SS2	0.618	0.666	0.639	**0.766**

Table 4.6 Cross loadings (continued)

	PB	SCI	SL	SS
SS3	0.637	0.677	0.625	**0.766**
SS4	0.707	0.717	0.690	**0.810**
SS5	0.633	0.631	0.647	**0.783**
SS6	0.645	0.694	0.667	**0.788**

Table 4.7 Model fit

Measure	Saturated model	Estimated model	Threshold	Interpretation
SRMR	0.053	0.053	<0.08	Excellent
d_ULS	0.427	0.427	<0.95	Excellent
d_G	0.256	0.256	<0.95	Excellent
Chi-square	406.894	406.894	-	-
NFI	0.964	0.964	>0.9	Excellent

4.2 Structural model

To generate t-statistics and standard errors, bootstrapping was used. The path coefficient for the endogenous variables and interpretable force (R-square, R2 for the endogenous variables) were then estimated using the relationship between the constructs and the question items in the structural model. R2 is a measure of the amount of variance explained by the model, like multiple regression. For the purpose of evaluating the research model, the path coefficient represents the connection relationship between the components and the influence strength between them, and the causal relationship between observed variables and potential variables was hypothetically calculated. As a result, SmartPLS bootstrapping was run 5000 times in order to obtain relevant results, as shown below.

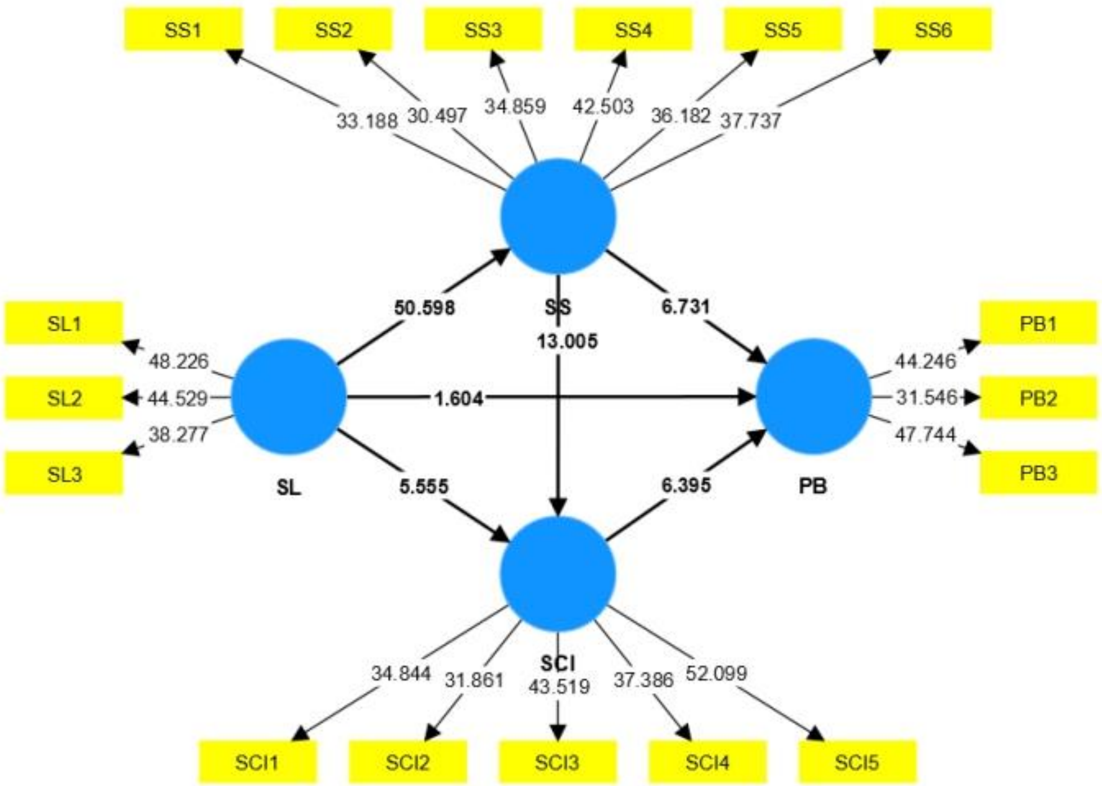

Figure 4.2 Results of bootstrapping executed

Table 4.8 R-square

	R-square	R-square adjusted
PB	0.734	0.731
SCI	0.777	0.775
SS	0.701	0.700

Through the significance pointer (t-value) in the model, the hypothesis between potential variables in this study can be verified, as shown below. t >1.96 at p < 0.05, t > 2.58, at p < 0.01, t > 3.29 at p < 0.001 for two-tailed tests. P>0.05 means not significant, p<0.05 indicates a correlation at 90% significance level, p<0.01 indicates a correlation at 99% significance level, and p<0.001 indicates a correlation at 99.9% significance level. The path analysis diagram shows the model of social learning, social support, social commerce intention and purchase behavior.

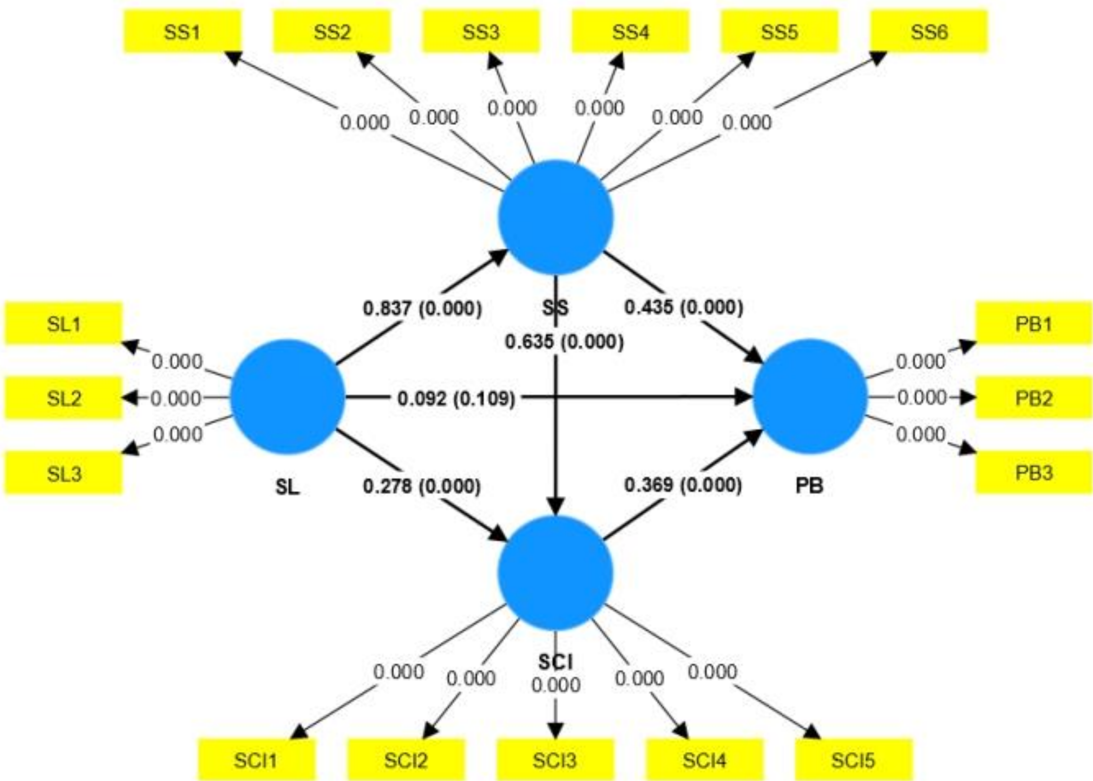

Figure 4.3 Results of path coefficients and P values

Note: All factor loadings are significant at $p < 0.05$.

Table 4.9 Verification of research hypothesis

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
SCI -> PB	**0.369**	0.371	0.058	6.395	0.000
SL -> PB	**0.092**	0.090	0.057	1.604	0.109
SL -> SCI	**0.278**	0.278	0.050	5.555	0.000
SL -> SS	**0.837**	0.838	0.017	50.598	0.000
SS -> PB	**0.435**	0.435	0.065	6.731	0.000
SS -> SCI	**0.635**	0.636	0.049	13.005	0.000

Note: □ Indicates regression impact relationship or measurement relationship. All factor loadings are significant at $p < 0.05$.

P<0.05 means significant, and $p < 0.001$ indicates a correlation at 99.9% significance level. Based on the results of the above correlation analysis, it can be seen that each variable (except SL -> PB) is significantly correlated at the 99.9% significance level ($p < 0.001$), and the correlation coefficients (the second column) are all greater than 0, so they are all positively correlated.

Social learning has a positive effect on social support (H1a) and has a positive effect on social commerce intention (H1b). P values are 0.000< 0.05 and path coefficients are positive (b=0.837>0 and b=0.635>0, respectively). And R-square value of social support is 0.701>0.67, it means that social learning can explain 70.1% of the changes in social support, which indicates that the explanatory power is quite strong. Social learning has no positive effect on purchase behavior (H1c) because social learning is not associated with purchase behavior. P value is 0.109>0.05 means this path does not show significance, indicating that social learning has no influence on purchase behavior. Social support has a positive effect on social commerce intention (H2a). P value is 0.000< 0.05 or t=13.005>1.96 means significance, and the path coefficient is 0.635>0, which means positive correlation. Social support has a positive effect on purchase behavior (H2b). P value is 0.000< 0.05 and the path coefficient is 0.435>0. The results of this study support this hypothesis. Social commerce intention has a positive effect on purchase behavior (H3). P value is 0.000< 0.05 and the R-square values of social commerce intention and purchase behavior are 0.777 and 0.734, respectively, it means that social learning and social support can explain 77.7% of the changes in social commerce intention and 73.4% of the changes in purchase behavior, showing quite strong explanatory power.

Therefore, social learning has a significant positive impact on social support and social commerce intention. Social support has a significant positive impact on social commerce intention and purchase behavior. Social commerce intention has a significant positive influence on purchase behavior. Social learning has no influence on purchase behavior.

Table 4.10 Results of research hypothesis

Hypothesis	Decision
H1a: SL -> SS	supported
H1b: SL -> SCI	supported
H1c: SL -> PB	not supported
H2a: SS -> SCI	supported
H2b: SS -> PB	supported
H3: SCI -> PB	supported

PLS-SEM analyses showed that all the paths (except for SL -> PB) in this research model were significant, while the R-square value indicated that the model would have sufficient explanatory power.

Table 4.11 Total effects

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
SCI -> PB	**0.369**	0.371	0.058	6.395	0.000
SL -> PB	**0.755**	0.755	0.023	32.239	0.000
SL -> SCI	**0.810**	0.810	0.018	44.276	0.000
SL -> SS	**0.837**	0.838	0.017	50.598	0.000
SS -> PB	**0.669**	0.671	0.054	12.298	0.000
SS -> SCI	**0.635**	0.636	0.049	13.005	0.000

Note: □ Indicates regression impact relationship or measurement relationship. All factor loadings are significant at $p < 0.05$.

Table 4.12 Total indirect effects

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
SL -> PB	**0.663**	0.665	0.045	14.624	0.000
SL -> SCI	**0.532**	0.533	0.043	12.478	0.000
SS -> PB	**0.234**	0.236	0.043	5.430	0.000

Note: □ Indicates regression impact relationship or measurement relationship. All factor loadings are significant at $p < 0.05$.

Table 4.13 Specific indirect effects

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
SL -> SS -> SCI -> PB	**0.196**	0.198	0.037	5.367	0.000
SS -> SCI -> PB	**0.234**	0.236	0.043	5.430	0.000

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
SL -> SS -> SCI	**0.532**	0.533	0.043	12.478	0.000
SL -> SCI -> PB	**0.103**	0.103	0.023	4.442	0.000
SL -> SS -> PB	**0.364**	0.364	0.053	6.822	0.000

Note: □ Indicates regression impact relationship or measurement relationship. All factor loadings are significant at $p < 0.05$.

Total effects are the sum of Total indirect effects plus direct effects. From the above figure, it is clear that since the direct effect of SL -> PB (H1c) is not significant (p=0.109>0.05), so this structural model is a fully mediated model, i.e., Social learning=> Social commerce intention=>Purchase behavior is fully mediated and Social learning=>Social support=>Purchase behavior is fully mediated. Therefore, although SL cannot have a direct effect on PB, it can have a significant indirect effect on PB through SS or SCI. And the correlation coefficients (the second column) are all greater than 0, so they are all positively correlated.

Table 4.14 LV prediction summary

	Q^2predict	RMSE	MAE
PB	**0.567**	0.663	0.527
SCI	**0.655**	0.592	0.464
SS	**0.699**	0.552	0.437

Table 4.15 MV prediction summary

	Q^2predict	PLS-SEM_RMSE	PLS-SEM_MAE	LM_RMSE	LM_MAE
PB1	**0.397**	0.983	0.788	0.990	0.791
PB2	**0.279**	1.020	0.814	1.025	0.822
PB3	**0.447**	0.925	0.742	0.929	0.742
SCI1	**0.411**	0.956	0.763	0.960	0.769

Table 4.15 MV prediction summary (continued)

	Q^2predict	PLS-SEM_RMSE	PLS-SEM_MAE	LM_RMSE	LM_MAE
SCI2	**0.363**	1.003	0.799	1.010	0.806
SCI3	**0.451**	0.918	0.753	0.922	0.761
SCI4	**0.402**	0.987	0.802	0.991	0.803
SCI5	**0.491**	0.915	0.725	0.921	0.730
SS1	**0.434**	0.965	0.762	0.970	0.769
SS2	**0.405**	0.985	0.785	0.991	0.789
SS3	**0.387**	0.977	0.767	0.982	0.771
SS4	**0.473**	0.965	0.759	0.965	0.758
SS5	**0.415**	0.960	0.765	0.961	0.765
SS6	**0.441**	0.942	0.752	0.947	0.757

The Q2 indicators used for model evaluation need to be calculated by blindfolding to obtain the results. Predictive relevance (Q^2)>0 means the latent variables can be predicted by the indicators, and the larger Q^2 is, the stronger the correlation is. From the above table, it can be seen that all the indicators have a strong ability to predict the correlation.

4.3 Analysis results

Overall, this study obtained a total of 300 valid sample questionnaires on WeChat, one of the most popular social platforms in China. An empirical study was conducted by using SEM-PLS. The results showed that 5 hypotheses were supported and H1c (social learning is positively correlated with purchase behavior) hypothesis was not supported.

(1) Social learning, social support, social commerce intention are significant predictors of purchase behavior and have significant positive impacts on consumers' purchase behavior.

(2) Social learning is a significant predictor of social support, social commerce intention and purchase behavior. It has a significant direct positive impact on social support and social commerce intention. It has a significant indirect positive impact on purchase behavior.

(3) Social support is a significant predictor of consumers' social commerce intention and has a significant positive effect on consumers' purchase behavior.

4.4 Sample analysis

4.4.1 Frequency analysis

Table 4.16 Attitude of social learning

Variable	Category	Frequency	Percentage (%)	Mean	SD
SL1	Strongly disagree	1	0.3	5.07	1.28
	Disagree	6	2.0		
	Relative disagree	29	9.7		
	Neutral	58	19.3		
	Relative agree	88	29.3		
	Agree	76	25.3		
	Strongly agree	42	14.0		
SL2	Strongly disagree	2	0.7	5.11	1.20
	Disagree	3	1.0		
	Relative disagree	24	8.0		
	Neutral	53	17.7		
	Relative agree	103	34.3		
	Agree	79	26.3		
	Strongly agree	36	12.0		
SL3	Strongly disagree	2	0.7	5.07	1.21
	Disagree	1	0.3		
	Relative disagree	23	7.7		

Variable	Category	Frequency	Percentage (%)	Mean	SD
	Neutral	72	24.0		
	Relative agree	93	31.0		
	Agree	68	22.7		
	Strongly agree	41	13.7		
	Total	300	100.0		

Note:

SL1=The forums and communities provided me with the information i needed for my last shopping experience.

SL2=The ratings and reviews provided me with the information i needed for my last shopping experience.

SL3=The social recommendations provided me with the information i needed for my last shopping experience.

From the above table, it can be seen that Learning from forums and communities (LFC) is mainly Relative agree with 29.3%, followed by Agree with 25.3%. Learning from ratings and reviews (LRR) is mainly Relative agree (34.3%), followed by Agree (26.3%). Learning from social recommendations (LSR) is mainly Relative agree (31.0%), followed by Neutral (24.0%).

In summary, the perception of social learning is mainly Relative agree.

Table 4.17 Attitude of social support

Variable	Category	Frequency	Percentage (%)	Mean	SD
SS1	Strongly disagree	1	0.3	5.18	1.28
	Disagree	7	2.3		
	Relative disagree	21	7.0		
	Neutral	54	18.0		

Variable	Category	Frequency	Percentage (%)	Mean	SD
	Relative agree	95	31.7		
	Agree	68	22.7		
	Strongly agree	54	18.0		
	Strongly disagree	1	0.3		
	Disagree	5	1.7		
	Relative disagree	29	9.7		
SS2	Neutral	57	19.0	5.09	1.28
	Relative agree	95	31.7		
	Agree	66	22.0		
	Strongly agree	47	15.7		
SS3	Strongly disagree	1	0.3	5.10	1.25

Table 4.17 Attitude of social support (continued)

Variable	Category	Frequency	Percentage (%)	Mean	SD
	Disagree	3	1.0		
	Relative disagree	24	8.0		
	Neutral	71	23.7		
	Relative agree	85	28.3		
	Agree	69	23.0		
	Strongly agree	47	15.7		
	Strongly disagree	2	0.7		
	Disagree	9	3.0		
	Relative disagree	18	6.0		
SS4	Neutral	56	18.7	5.19	1.33
	Relative agree	86	28.7		
	Agree	73	24.3		
	Strongly agree	56	18.7		
SS5	Strongly disagree	2	0.7	5.18	1.25

Variable	Category	Frequency	Percentage (%)	Mean	SD
	Disagree	4	1.3		
	Relative disagree	20	6.7		
	Neutral	58	19.3		
	Relative agree	96	32.0		
	Agree	69	23.0		
	Strongly agree	51	17.0		
	Strongly disagree	1	0.3		
	Disagree	6	2.0		
	Relative disagree	24	8.0		
SS6	Neutral	55	18.3	5.14	1.26
	Relative agree	94	31.3		
	Agree	74	24.7		
	Strongly agree	46	15.3		
	Total	300	100.0		

Note:

SS1=When I encountered a problem, some people on the s-commerce platform would give me information to help me overcome the problem.

SS2=When faced with difficulties, some people on the s-commerce platform would help me discover the cause and provide me with suggestions.

SS3=When faced with difficulties, some people on the s-commerce platform comforted and encouraged me.

SS4=When faced with difficulties, some people on the s-commerce platform listened to me talk about my private feelings.

SS5=When faced with difficulties, some people on the s-commerce platform expressed interest and concern in my well-being.

SS6=When faced with difficulties, some people on the s-commerce platform helped me to solve the problem.

From the above table, SS1's view is mainly Relative agree with 31.7%, followed by Agree with 22.7%. SS2's view is mainly Relative agree, accounting for 31.7%, followed by Agree, accounting for 22.7%. SS3's view was mainly Relative agree, with 28.3%, followed by Neutral, with 23.7%. SS4's view was mainly Relative agree, with 28.7%, followed by Agree, with 24.3%. SS5's view was mainly Relative agree with 32.0%, followed by Agree with 23.0%. For SS6, Relative agree was the main opinion, accounting for 31.3%, followed by Agree, accounting for 24.7%. In summary, Informational support (IS) includes SS1 and SS2, with Relative agree being the main view. Emotional support (ES) includes SS3, SS4 and SS5, which are mainly seen as Relative agreement. Tangible support (TS) includes SS6, which is seen as Relative agree.

Therefore, the social support view is mainly Relative agree.

Table 4.18 Attitude of social commerce intention

Variable	Category	Frequency	Percentage (%)	Mean	SD
SCI1	Strongly disagree	0	0.0	5.08	1.24
	Disagree	5	1.7		
	Relative disagree	30	10.0		
	Neutral	59	19.7		
	Relative agree	90	30.0		
	Agree	75	25.0		

Variable	Category	Frequency	Percentage (%)	Mean	SD
	Strongly agree	41	13.7		
	Strongly disagree	0	0.0		
	Disagree	8	2.7		
	Relative disagree	25	8.3		
SCI2	Neutral	49	16.3	5.15	1.25
	Relative agree	95	31.7		
	Agree	79	26.3		
	Strongly agree	44	14.7		
	Strongly disagree	0	0.0		
	Disagree	6	2.0		
	Relative disagree	19	6.3		
SCI3	Neutral	54	18.0	5.24	1.24
	Relative agree	92	30.7		
	Agree	75	25.0		
	Strongly agree	54	18.0		
	Strongly disagree	1	0.3		
	Disagree	7	2.3		
	Relative disagree	23	7.7		
SCI4	Neutral	64	21.3	5.08	1.27
	Relative agree	94	31.3		
	Agree	64	21.3		
	Strongly agree	47	15.7		
SCI5	Strongly disagree	1	0.3	5.12	1.28
	Disagree	13	4.3		

Table 4.18 Attitude of social commerce intention (continued)

Variable	Category	Frequency	Percentage (%)	Mean	SD
	Relative disagree	18	6.0		

Variable	Category	Frequency	Percentage (%)	Mean	SD
	Neutral	51	17.0		
	Relative agree	89	29.7		
	Agree	91	30.3		
	Strongly agree	37	12.3		
	Total	300	100.0		

Note:

SCI1=I am willing to provide my experiences and suggestions when my friends on the s-commerce platform want my advice on buying something.

SCI2=I am willing to share my own shopping experience with my friends on the s-commerce platform.

SCI3=I am willing to consider the shopping experiences of my friends on the s-commerce platform when I want to shop.

SCI4=I am willing to ask my friends on the s-commerce platform to provide me with their suggestions before I go shopping.

SCI5=I am willing to buy the products recommended by my friends on the s-commerce platform.

From the above table, it can be seen that the view of SCI1 is mainly Relative agree with 30.0%, followed by Agree with 25.0%. The view of SCI2 is mainly Relative agree, accounting for 31.7%, followed by Agree, accounting for 26.3%. The view of SCI3 was mainly Relative agree with 30.7%, followed by Agree with 25.0%. The view of SCI4 was mainly Relative agree with 31.3%, followed by Agree and Neutral, both with 21.3%. The view of SCI5 was mainly Agree, with 30.3%, followed by Relative agree, with 29.7%.

In summary, the view of social commerce intention is mainly relative agree.

Table 4.19 Attitude of purchase behavior

Variable	Category	Frequency	Percentage (%)	Mean	SD
	Strongly disagree	1	0.3		
	Disagree	7	2.3		
	Relative disagree	20	6.7		
PB1	Neutral	61	20.3	5.14	1.26
	Relative agree	92	30.7		
	Agree	71	23.7		
	Strongly agree	48	16.0		
	Strongly disagree	0	0.0		
	Disagree	6	2.0		
	Relative disagree	19	6.3		
PB2	Neutral	69	23.0	5.08	1.20
	Relative agree	99	33.0		
	Agree	65	21.7		
	Strongly agree	42	14.0		
	Strongly disagree	1	0.3		
	Disagree	2	0.7		
	Relative disagree	27	9.0		
PB3	Neutral	54	18.0	5.20	1.24
	Relative agree	87	29.0		
	Agree	80	26.7		
	Strongly agree	49	16.3		
	Total	300	100.0		

Note:

PB1=I will use the s-commerce platform to find the products I like.

PB2=I will buy the products or services on the s-commerce platform.

PB3=I will recommend a product that is worth buying to my friends on the s-commerce platform.

From the above table, it can be seen that the opinion of PB1 is mainly Relative agree with 30.7%. The opinion of PB2 is mainly Relative agree, accounting for 33.0%. The opinion of PB3 is mainly Relative agree, accounting for 29.0%.

In conclusion, the perception of purchase behavior is mainly Relative agree.

4.4.2 Summary

In summary, the opinions of the samples with different gender, age, education level, occupation, and income levels about social learning, social support, social commerce intention, and purchase behavior were mainly relative agree.

4.5 Test of Variance

By using independent sample t-tests, chi-square tests, and one-way ANOVAs, tests of variance can be performed to determine the differences in variable dimensions. Based on the characteristics of the data, independent sample t-tests and one-way ANOVA were used.

Table 4.20 Analysis of the differences between dimensions in terms of gender

Variable	Category	N	Mean	SD	t	sig
Social learning	Male	146	15.36	3.071	0.574	**0.283**
	Female	154	15.16	2.969		
Social support	Male	146	31.36	5.982	1.345	**0.090**
	Female	154	30.43	5.962		
Social commerce intention	Male	146	25.88	4.938	0.721	**0.236**
	Female	154	25.45	5.196		
Purchase behavior	Male	146	15.68	2.991	1.502	**0.067**
	Female	154	15.16	3.032		

The t-test investigates the difference of X (definite category, 2 groups) for Y (quantitative). Based on the results of the above independent sample t-test, we can see the difference of each dimension in terms of gender. P>0.05 means not significant. The significance test results of SL is 0.283, SS is 0.090, SCI is 0.236, and PB is 0.067, which means that different gender samples do not show significance (p>0.05) for social learning, social support, social commerce intention, and purchase behavior. This means that consumers of different genders show consistency in all four dimensions and there is no significant difference.

Table 4.21 Analysis of the differences between dimensions in terms of age

Variable	Category	N	Mean	SD	F	sig	Multiple comparisons
Social learning	Below 18	42	15.26	3.013	1.866	**0.100**	/
	18-25	59	16.05	2.549			
	26-30	71	14.94	2.853			
	31-35	57	14.53	3.213			
	36-40	50	15.66	3.134			
	Above 40	21	15.05	3.584			
Social support	Below 18	42	30.81	5.688	1.34	**0.247**	/
	18-25	59	32.1	5.281			
	26-30	71	30.75	5.975			
	31-35	57	29.46	6.33			
	36-40	50	31.58	6.36			
	Above 40	21	30.24	6.26			
Social commerce intention	Below 18	42	25.31	5.029	1.574	**0.167**	/
	18-25	59	26.68	4.805			
	26-30	71	25.49	5.051			
	31-35	57	24.44	5.471			
	36-40	50	26.58	4.887			

Variable	Category	N	Mean	SD	F	sig	Multiple comparisons
	Above 40	21	25.19	4.854			
Purchase behavior	Below 18	42	15.14	2.781	0.955	**0.446**	/
	18-25	59	15.81	2.549			
	26-30	71	15.52	3.211			
	31-35	57	14.77	3.134			
	36-40	50	15.78	3.183			
	Above 40	21	15.38	3.309			

P>0.05 means not significant. Based on the above one-way ANOVA results, it can be seen from the above table that: none of the different age samples will show significant for social learning (p=0.100), social support (p=0.247), social commerce intention (p=0.167), purchase behavior (p=0.446), implying that different age samples do not show significant differences for all four dimensions. this means that the social commerce platform takes into account all age groups of consumers and maximizes the purchasing needs of all age groups, so age is not a factor that affects consumers' purchasing intention and purchasing behavior.

Table 4.22 Analysis of the differences between dimensions in terms of education level

Variable	Category	N	Mean	SD	F	sig	Multiple comparisons
Social learning	High school and below	88	15.53	2.808	0.536	**0.658**	/
	Vocational diploma	100	15.26	3.05			
	Bachelor	102	15.07	3.032			
	Master and above	10	14.6	4.326			
Social support	High school and below	88	31.6	5.275	1.361	**0.255**	/
	Vocational diploma	100	31.17	6.179			
	Bachelor	102	30.17	5.979			
	Master and above	10	28.9	9.036			

Social commerce intention	High school and below	88	26.05	4.673	1.233	**0.298**	/
	Vocational diploma	100	26.09	5.049			
	Bachelor	102	25.07	5.198			
	Master and above	10	24	6.928			
Purchase behavior	High school and below	88	15.51	2.729	1.691	**0.169**	/
	Vocational diploma	100	15.8	3.018			
	Bachelor	102	15.1	2.993			
	Master and above	10	14	4.989			

P>0.05 means not significant. Based on the results of the above one-way ANOVA, it can be seen that the samples with different education levels do not show significant differences for social learning (p=0.658), social support (p=0.255), social commerce intention (p=0.298), and purchase behavior (p=0.169).

Table 4.23 Analysis of the differences between dimensions in terms of occupation

Variable	Category	N	Mean	SD	F	sig	Multiple comparisons
Social learning	Civil servants/public institution personnel	24	15.38	2.826	1.257	**0.287**	/
	Enterprise staff	92	15.54	2.853			
	Self-employed person	41	15.44	3.362			
	freelancer	81	14.62	3.215			
	Student	62	15.48	2.774			
Social support	Civil servants/public institution personnel	24	30.71	6.28	1.261	**0.286**	/
	Enterprise staff	92	31.71	5.27			
	Self-employed person	41	30.63	6.526			
	freelancer	81	29.77	6.545			
	Student	62	31.34	5.651			

Variable	Category	N	Mean	SD	F	sig	Multiple comparisons
Social commerce intention	Civil servants/public institution personnel	24	25.63	4.421	1.752	**0.139**	/
	Enterprise staff	92	26.6	4.648			
	Self-employed person	41	24.98	5.227			
	freelancer	81	24.72	5.494			
	Student	62	25.97	5.086			
Purchase behavior	Civil servants/public institution personnel	24	15.67	2.479	0.833	**0.505**	/
	Enterprise staff	92	15.8	2.833			
	Self-employed person	41	15.1	3.499			
	freelancer	81	15.05	3.305			
	Student	62	15.44	2.744			

P>0.05 means not significant. Based on the results of the above one-way ANOVA, it can be seen that the samples of different occupations do not show significant differences for social learning (p=0.287), social support (p=0.286), social commerce intention (p=0.139), and purchase behavior (p=0.505).

Table 4.24 Analysis of the differences between dimensions in terms of income

Variable	Category	N	Mean	SD	F	sig	Multiple comparisons
Social learning	Below 5000	134	15.49	2.846	0.995	**0.410**	/
	5001-10000	99	15.13	2.965			
	10001-15000	50	14.76	3.426			
	15001-20000	14	16	3.282			
	Above 20000	3	13.67	3.786			
Social support	Below 5000	134	31.31	5.652	2.138		/

Variable	Category	N	Mean	SD	F	sig	Multiple comparisons
	5001-10000	99	31.05	5.567			
	10001-15000	50	29.08	7.14		**0.076**	
	15001-20000	14	32.93	6.057			
	Above 20000	3	26.67	8.083			
Social commerce intention	Below 5000	134	25.87	5.066	0.805	**0.523**	/
	5001-10000	99	25.89	4.497			
	10001-15000	50	24.58	5.935			
	15001-20000	14	26.29	5.384			
	Above 20000	3	24	7			
Purchase behavior	Below 5000	134	15.49	2.82	0.942	**0.440**	/
	5001-10000	99	15.58	2.918			
	10001-15000	50	14.88	3.42			
	15001-20000	14	15.93	3.474			
	Above 20000	3	13.33	5.859			

P>0.05 means not significant. Based on the results of the above one-way ANOVA, it can be seen that the samples with different income levels do not show significant differences for social learning (p=0.410), social support (p=0.076), social commerce intention (p=0.523), and purchase behavior (p=0.440).

Therefore, the samples with different gender, age, education level, occupation, and income levels do not show any significant differences for social learning, social support, social commerce intention, and purchase behavior. The differences in social learning, social support, social commerce intention, and purchase behavior were not significant.

4.6 Summary

At this point, half of this study has been completed. Based on 300 valid sample questionnaires obtained from the WeChat social platform, we conducted a theoretical study. Based on social learning theory and social support theory, we constructed a structural equation model (PLS-SEM) relating social commerce intention and consumer behavior, and verified our research hypotheses. The study found that social learning is positively correlated with social support, social commerce intentions, and consumer purchase behavior, but social learning's effect on purchasing behavior is indirect rather than direct. Furthermore, social support affects social commerce intention, and social support affects purchase behavior as well.

The findings of our study are consistent with previous studies in the literature. As an example, [9] statistical analysis results indicate that social learning and social support are positively associated with social commerce intention, while social support is positively associated with social commerce intention. Also, [42] demonstrate that social support and social learning affect purchase intentions and decisions. There was significant correlation between social support constructs and social commerce in the form of learning from forums, communities, reviews, and social advertising. On social networking sites, social support constructs such as informational support and emotional support are significant in predicting consumer purchases. However, their study only stopped at the relationship between social learning, social support, and purchase intention, and did not further investigate their relationship with purchase behavior. Although purchase intention is an important indicator of customers' purchasing behavior, purchase intention is not equivalent to actual purchasing behavior. In contrast, the structural model constructed in this study demonstrates the relationship between social learning and social support with social commerce intention and purchase behavior, and points out that social learning is related to purchase behavior through social support and social commerce intention, and this relationship is positive, indirect, and significantly influences the relationship. It is also demonstrated that social learning, social support, and social commerce intention are important indicators of purchase behavior and can predict consumers' purchase behavior.

In addition, we also conducted a difference-in-differences analysis on the sample by SPSS to verify the consistency between our theoretical results and consumers' actual behaviors. The results of the statistical analysis show that consumers do not show significant differences between social learning and social support and social commerce intention and purchase behavior, and are relatively satisfied with all the measures in the structural model, proving that social learning and social support do facilitate consumers' social interactions, social commerce intention and actual purchase behavior.

Next, we will conduct the second part of the study. We believe that experiments can be understood in concrete cases and experimental results can guide practice, so we will analyze Chinese social e-commerce platforms and use Pinduoduo, one of the most popular social commerce platforms in China, as a case study. We will apply Philip Kotler's 5A Customer Behavior Path theory and analyze the actual social commerce behavior of the sample through SPSS statistical method.

CHAPTER 5

CASE STUDY

5.1 Chinese social commerce platforms

5.1.1 Background

Since 2021, social e-commerce has been put to the test. Traditional e-commerce platforms are accelerating into social e-commerce, and some social e-commerce platforms are frequently favored by capital, making the industry reshuffle intensify, from the peak to the shock adjustment period.

Social commerce in China is defined as a branch of digital retailing, narrowly defined as the act of buying and selling goods through social interaction by means of social networking sites and online media communication. The 2021 China Social E-Commerce Market Data Report [3] classifies China's social e-commerce into six categories: 1) shopping category: Pinduoduo, JD jingxi, Taote, Suning Shopping, etc.; 2) distribution category: Aikucun, FenXiang, Peanut Diary, Future Bazaar, Darling Home, O'MALL, etc.; 3) community + e-commerce category: Xiaohongshu, Baby Tree, etc.; 4) shopping guide rebate category: Yitao, Fanli.com, VeiXiangKe, etc.; 5) membership category: Yunji, etc, zebra membership, honey bud Plus, etc.; (6) service category: Youzan, Weimeng, etc.

According to the 2021 China Social E-Commerce Market Data Report [3], the total amount of financing for social e-commerce in China in 2021 was 3.91 billion yuan, up 501.53% from 650 million yuan in the same period last year. In 2021, there will be three social e-commerce unicorns, namely Xiaohongshu ($20 billion), Weidian ($1.5 billion) and Whaling Group ($1 billion), with a total valuation of $22.5 billion. Compare this to the four social e-commerce "unicorns" in 2020, with a total valuation of $9.5 billion.

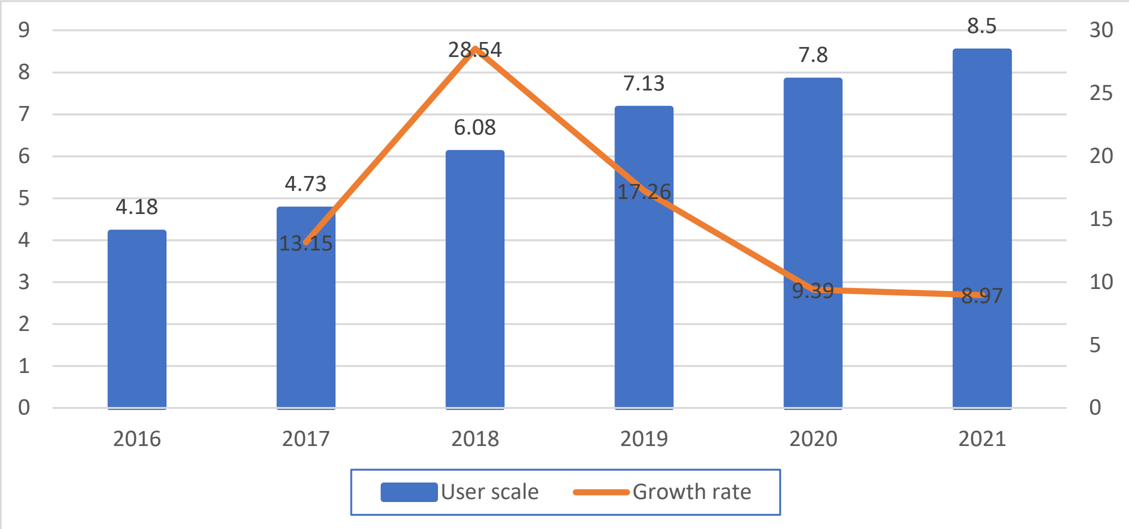

Figure 5.1 User scale and growth rate of social commerce industry [3]

In 2021, the user scale reached 850 million people, an increase of 8.97%, the growth rate declined. 2017 to 2018, social e-commerce user scale gradually increased, the user scale from 473 million to 608 million people, up to 28.54%. 2018 after the growth rate declined, 2019 and 2020 growth rate of 17.26%, 9.39%, respectively. According to the 48th Statistical Report on the Development of China's Internet, the average value of Internet applications in the subjective perceptions of digital consumers shows an inverse tick-shaped relationship with their age. Specifically, the value of Internet applications in the minds of 20-29 year old is the highest, 37.6% and 27.7% higher than that of 10-19 year old and 30-39 year old, respectively. As the natives of the Internet era, the 20-29 year old have stronger digital consumption ability and awareness, and their lifestyle needs (e.g. online shopping) and spiritual needs (e.g. online social networking) are satisfied on the Internet, and they recognize the value of the Internet very much.

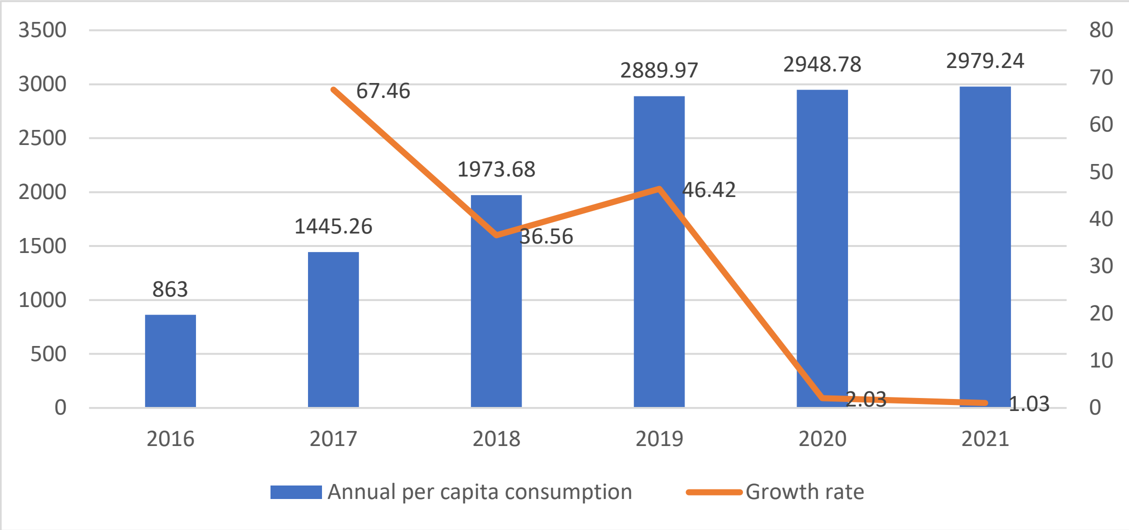

Figure 5.2 The annual per capita consumption and growth rate of social commerce industry [3]

The annual per capita consumption of social e-commerce in 2021 is 2,979.24 yuan, an increase of 1.03%, and the growth rate is on an upward trend. Meanwhile, the growth rates from 2017-2020 are 67.46%, 35.65%, 46.42% and 2.03%, respectively.

As of June 2021, the size of China's mobile internet users was 1.007 billion, with 99.6% of internet users using cell phones to access the internet and 26.9 hours per capita per week. In addition, the top four APPs in terms of mobile application scale accounted for 58.2% of the total. Among them, the number of e-commerce APPs and social communication APPs reached 295,000 and 271,000 respectively, ranking third and fourth in terms of mobile application scale, accounting for 9.8% and 9.0% of all APPs respectively [2].

The national economy's sustained and stable growth is driven by digital consumption. As e-commerce sinks to the fourth and fifth tiers of cities and villages, it facilitates two-way consumer exchanges, bridging urban and rural areas, and enhancing digital convenience in the sinking areas. Due to the increasing number of younger and older Internet users, and their increasing consumption capacity, the consumption demand in specific markets will increase, such as medical and health care, and e-sports, which will result in a new consumption pattern.

5.1.2 Sample Analysis

5.1.2.1 Frequency analysis

Table 5.1 Demographic information of respondents

Variable	Category	Frequency	Percentage (%)
	Guangzhou	77	25.7
	Shenzhen	55	18.3
	Dongguan	22	7.3
	Zhuhai	20	6.7
	Foshan	18	6.0
	Zhongshan	13	4.3
	Huizhou	12	4.0
	Shantou	12	4.0
	Yangjiang	8	2.7
	Zhanjiang	8	2.7
City	Meizhou	7	2.3
	Qingyuan	7	2.3
	Jieyang	6	2.0
	Maoming	6	2.0
	Jiangmen	5	1.7
	Heyuan	5	1.7
	Zhaoqing	5	1.7
	Yunfu	4	1.3
	Shaoguan	4	1.3
	Chaozhou	3	1.0
	Shanwei	3	1.0
	Total	300	100.0

The geographical distribution of the sample by frequency statistics, as can be seen from the above table, is mostly from the cities of Guangzhou and Shenzhen, accounting for 25.7% and 18.3% respectively. They are the two most economically developed cities in Guangdong Province, and also the two most developed cities in China besides Beijing and Shanghai.

Table 5.2 Social commerce platform used

Variable	Category	Frequency	Response rate	Popularity rate
	Wechat	94	20.80%	31.30%
	Weibo	59	13.10%	19.70%
	Pinduoduo	63	14.00%	21.00%
	Xiaohongshu	48	10.60%	16.00%
S-commerce platform used (multiple responses)	JD	51	11.30%	17.00%
	Tiktok	48	10.60%	16.00%
	Yunji	39	8.60%	13.00%
	Beidian	23	5.10%	7.70%
	O'MALL	26	5.80%	8.70%
	Others	0	0	0
	Total	451	100.00%	150.30%

Goodness-of-fit test: $\chi 2=86.966$, $p=0.000$

In order to determine whether the proportion of multiple-choice options was evenly distributed, we used the chi-square goodness-of-fit test. The goodness-of-fit test indicates that there are significant differences in the proportions of choices of each item (chi=86.966, $p=0.000<0.05$), so using multiple responses is an effective way to analyze these differences. The proportion of choices for each multiple choice question was analyzed through multiple response analysis. Response rate indicates the relative selection ratio between options. Popularity rate measures a particular item's popularity. However, the number of divisors varies between the two. Wechat, Weibo, and Pinduoduo have a significantly higher response rate and popularity rate.

Table 5.3 Frequency of using s-commerce platforms

Variable	Category	Frequency	Percentage (%)	Mean	SD
Frequency of using s-commerce platforms	More than once a day	168	56	1.84	1.17
	Once a day	66	22		
	4-6 times a week	24	8		
	1-3 times a week	30	10		
	1-3 times a month	12	4		
	Never	0	0		
	Total	300	100		

As we can see from the above table, the frequency of using s-commerce platforms is mainly More than once a day, accounting for 56%, followed by Once a day, accounting for 22%.

Table 5.4 Buying Behavior type on the s-commerce platform

Variable	Category	Frequency	Response rate	Popularity rate
Buying behavior type (multiple responses)	Complex buying behavior	111	25.40%	37.00%
	Dissonance buying behavior	53	12.10%	17.70%
	Variety seeking behavior	145	33.20%	48.30%
	Habitual buying behavior	128	29.30%	42.70%
	Total	437	100.00%	145.70%

Goodness-of-fit test： $\chi 2=30.383$ $p=0.000$

Using the chi-square goodness-of-fit test for uniformity, the distribution of the proportion of choices for each multiple choice question was analyzed. As shown in the table above, the goodness-of-fit test was significant (chi=30.383, $p=0.000<0.05$), indicating that the proportion of choices was significantly different for each item. This difference could be compared by response rate or prevalence rate. In particular, the response rate and prevalence rates were significantly higher for two items, variety seeking behavior and habitual buying behavior.

In summary, the sample is mainly distributed in Guangzhou, followed by Shenzhen. The frequency of using s-commerce platforms is More than once a day, and the type of buying behavior is mainly Variety seeking behavior, followed by Habitual buying behavior.

5.1.2.2 Analysis of variance

The following statistical results were obtained by cross-tabulation analysis and one-way ANOVA.

Table 5.5 Analysis of the variability of gender under different types of purchasing behavior

Variable	Category	Gender				Total		t	sig
		Male		Female					
1.Complex buying behavior	No	90	30%	99	33%	189	63%	0.47	**0.32**
	Yes	56	19%	55	18%	111	37%		
2.Dissonance buying behavior	No	119	40%	128	43%	247	82%	0.36	**0.36**
	Yes	27	9%	26	9%	53	18%		
3.Variety seeking behavior	No	81	27%	74	25%	155	52%	-1.29	**0.10**
	Yes	65	22%	80	27%	145	48%		
4.Habitual buying behavior	No	82	27%	90	30%	172	57%	0.40	**0.35**
	Yes	64	21%	64	21%	128	43%		
Total		146	49%	154	51%	300	100%		

P>0.05 means not significant. As can be seen from the above table, all sig are more than 0.05 (0.32, 0.36, 0.10, 0.35, respectively), indicating that there is no significant difference between gender and the four different types of buying behavior.

In addition, 1. Complex buying behavior, 2. Dissonance buying behavior, 4. Habitual buying behavior males and females showed the same behavior and there was no difference. 3.Variety seeking behavior, 27% of females and 22% of males, females were higher than males.

Table 5.6 Analysis of the variability of age under different types of purchasing behavior

Variable	Category	Age												Total		F	sig
		Below 18		18-25		26-30		31-35		36-40		Above 40					
1.Complex buying behavior	No	26	9%	36	12%	39	13%	42	14%	31	10%	15	5%	189	63%	1.110	**0.355**
	Yes	16	5%	23	8%	32	11%	15	5%	19	6%	6	2%	111	37%		
2.Dissonance buying behavior	No	32	11%	49	16%	62	21%	45	15%	41	14%	18	6%	247	82%	0.583	**0.713**
	Yes	10	3%	10	3%	9	3%	12	4%	9	3%	3	1%	53	18%		
3.Variety seeking behavior	No	19	6%	34	11%	38	13%	26	9%	28	9%	10	3%	155	52%	0.590	**0.707**
	Yes	23	8%	25	8%	33	11%	31	10%	22	7%	11	4%	145	48%		
4.Habitual buying behavior	No	23	8%	35	12%	42	14%	34	11%	28	9%	10	3%	172	57%	0.251	**0.939**
	Yes	19	6%	24	8%	29	10%	23	8%	22	7%	11	4%	128	43%		
Total		42	14%	59	20%	71	24%	57	19%	50	17%	21	7%	300	100%		

P>0.05 means not significant. As can be seen from the above table, all sig are more than 0.05 (0.355, 0.713, 0.707, 0.939, respectively), indicating that there is no significant difference between age and the four different types of purchasing behavior.

In addition, 1. Complex buying behavior, 26-30 is the most, accounting for 11%. 2. Dissonance buying behavior, 31-35 was the most, accounting for 4%. 3. Variety seeking behavior, 26-30 and 31-35, accounted for 11% and 10% respectively. 4. Habitual buying behavior, 26-30 is the most, accounting for 10%.

Therefore, for different buying behaviors, 26-30 is the main group of complex buying behavior and variety seeking behavior.

Table 5.7 Analysis of the variability of education level under different types of purchasing behavior

Variable	Category	Education Level								Total		F	sig
		High school and below		Vocational diploma		Bachelor		Master and above					
1.Complex buying behavior	No	57	19%	56	19%	68	23%	8	3%	189	63%	1.35	**0.26**
	Yes	31	10%	44	15%	34	11%	2	1%	111	37%		
2.Dissonance buying behavior	No	73	24%	87	29%	77	26%	10	3%	247	82%	2.34	**0.07**
	Yes	15	5%	13	4%	25	8%	0	0%	53	18%		
3.Variety seeking behavior	No	42	14%	58	19%	51	17%	4	1%	155	52%	0.93	**0.43**
	Yes	46	15%	42	14%	51	17%	6	2%	145	48%		
4.Habitual buying behavior	No	49	16%	55	18%	63	21%	5	2%	172	57%	0.45	**0.72**
	Yes	39	13%	45	15%	39	13%	5	2%	128	43%		
Total		88	29%	100	33%	102	34%	10	3%	300	100%		

P>0.05 means not significant. As can be seen from the table above, all sig are more than 0.05 (0.26, 0.07, 0.43, 0.72, respectively), indicating that there is no significant difference between education level and the four different types of purchasing behavior.

In addition, 1. Complex buying behavior, Vocational diploma is the most, accounting for 15%. 2. Dissonance buying behavior, Bachelor was the most, accounting for 8%. 3. Variety seeking behavior, Bachelor has the most, accounting for 17%. 4. Habitual buying behavior, Vocational diploma is the most, accounting for 15%.

Therefore, for different buying behavior, bachelor is the main group of variety seeking behavior.

Table 5.8 Analysis of the variability of occupation under different types of purchasing behavior

Variable	Category	Occupation										Total		F	sig
		Civil servants		Enterprise staff		Self-employed person		freelancer		Student					
1.Complex buying behavior	No	14	5%	55	18%	31	10%	49	16%	40	13%	189	63%	0.92	**0.45**
	Yes	10	3%	37	12%	10	3%	32	11%	22	7%	111	37%		
2.Dissonance buying behavior	No	21	7%	73	24%	34	11%	71	24%	48	16%	247	82%	0.90	**0.46**
	Yes	3	1%	19	6%	7	2%	10	3%	14	5%	53	18%		
3.Variety seeking behavior	No	17	6%	50	17%	17	6%	42	14%	29	10%	155	52%	1.53	**0.19**
	Yes	7	2%	42	14%	24	8%	39	13%	33	11%	145	48%		
4.Habitual buying behavior	No	9	3%	62	21%	24	8%	43	14%	34	11%	172	57%	2.14	**0.08**
	Yes	15	5%	30	10%	17	6%	38	13%	28	9%	128	43%		
Total		24	8%	92	31%	41	14%	81	27%	62	21%	300	100%		

P>0.05 means not significant. As can be seen from the above table, all sig are more than 0.05 (0.45, 0.46, 0.19, 0.08, respectively), indicating that there is no significant difference between occupation and the four different types of purchasing behavior.

In addition, 1. Complex buying behavior, Enterprise staff and Freelancer have the most, with 12% and 11% respectively. 2. Dissonance buying behavior, Enterprise staff and Student had the most, with 6% and 5% respectively. 3. Variety seeking behavior, Enterprise staff and Freelancer have the most, accounting for 14% and 13% respectively. 4. Habitual buying behavior, Freelancer has the most, accounting for 13%.

Therefore, enterprise staff is the main group of variety seeking behavior for different buying behaviors.

Table 5.9 Analysis of the variability of income under different types of purchasing behavior

Variable	Category	Income										Total		F	sig
		Below 5000		5001-10000		10001-15000		15001-20000		Above 20000					
1.Complex buying behavior	No	87	29%	60	20%	33	11%	7	2%	2	1%	189	63%	0.42	**0.80**
	Yes	47	16%	39	13%	17	6%	7	2%	1	0%	111	37%		
2.Dissonance buying behavior	No	107	36%	83	28%	41	14%	13	4%	3	1%	247	82%	0.60	**0.66**
	Yes	27	9%	16	5%	9	3%	1	0%	0	0%	53	18%		
3.Variety seeking behavior	No	66	22%	55	18%	27	9%	7	2%	0	0%	155	52%	1.06	**0.38**
	Yes	68	23%	44	15%	23	8%	7	2%	3	1%	145	48%		
4.Habitual buying behavior	No	77	26%	58	19%	28	9%	8	3%	1	0%	172	57%	0.20	**0.94**
	Yes	57	19%	41	14%	22	7%	6	2%	2	1%	128	43%		
Total		134	45%	99	33%	50	17%	14	5%	3	1%	300	100%		

P>0.05 means not significant. As can be seen from the table above, all sig are more than 0.05 (0.80, 0.66, 0.38, 0.94, respectively), indicating that there is no significant difference between income and the four different types of purchasing behavior.

In addition, 1.Complex buying behavior, Below 5000 is the most, accounting for 16%. 2. Dissonance buying behavior, below 5000 is the most, accounting for 9%. 3. Variety seeking behavior, below 5000, accounting for 23%. 4. Habitual buying behavior, below 5000 is the most, accounting for 19%.

Therefore, for different buying behaviors, below 5000 is the main group of variety seeking behavior.

5.1.3 Summary

In summary, when we applied SPSS statistical methods to the frequency statistics and variance analysis of consumers' purchasing behavior on Chinese social e-commerce platforms from 300 valid sample questionnaires, we arrived at a consumer portrait that, female, 26-30, bachelor, enterprise staff, below 5000, and variety seeking behavior are the main groups among all social commerce platform consumers. We believe this will help guide the improvement of business models, product marketing, and business strategies for social commerce platforms.

Next, we will apply Philip Kotler's 5A Customer Behavior Path theory to Pinduoduo, a leading social e-commerce platform in China, as a case study in hopes of conducting further social commerce purchase decision and behavior research on the sample through SPSS statistical methods.

5.2 Pinduoduo case study

5.2.1 Background

According to iiMedia Research [43], among the most frequently used social retail platforms by Chinese consumers, the top five are, in order, Pinduoduo, JD, Guomei, Yunji and O'MALL, with Pinduoduo and JD accounting for 69.1% and 65.0% respectively.

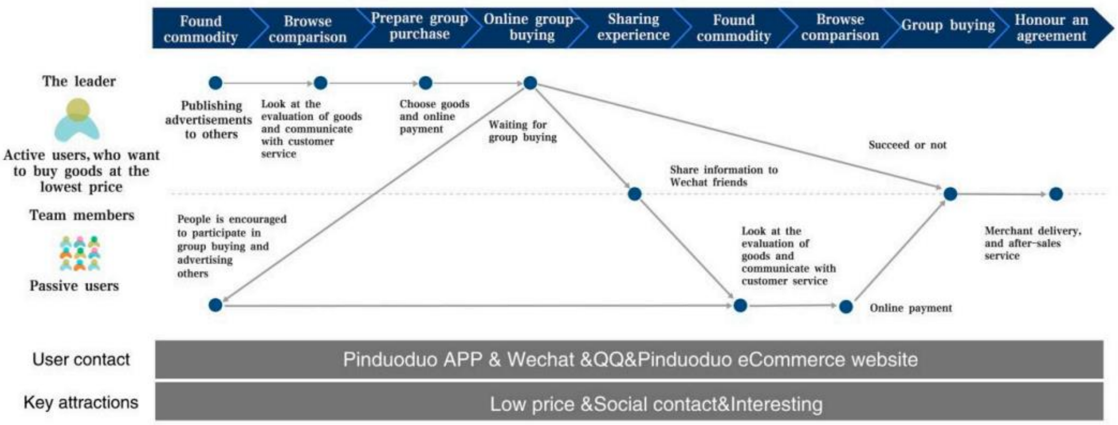

Figure 5.3 Purchase process on Pinduoduo platform [44]

The Pinduoduo platform believes that the people at the bottom of the pyramid (BOP) have huge business potential, which is why it starts with the BOP group as its primary demand-side users. When analyzing the consumer behavior characteristics of the BOP group, the company determined that they tend to consume based on their daily needs, are very sensitive to price, and only consume products that fit their basic needs and are within their acceptable price range. Therefore, the motivation strategy of "Low Price + Social Contact" was developed. Low price is the main reason to attract consumers to buy, consumers can choose to buy direct mode and group purchase mode, because the group purchase mode can make them buy below the market price, so the rapid delivery of product information through social media is the key to promote consumers to buy. There are four main categories of people who play a role in spreading information on the PDD platform: key opinion leader (KOL)， family and friends, a location-based relationship related parties (LBS) (such as fellow villagers/neighbors), and friend of a friend (FOAF). As a result of social media (such as Wechat), BOPs often share group buy advertisements to reach the minimum number of people needed for a group buy and then obtain a lower price through a more efficient distribution process (44).

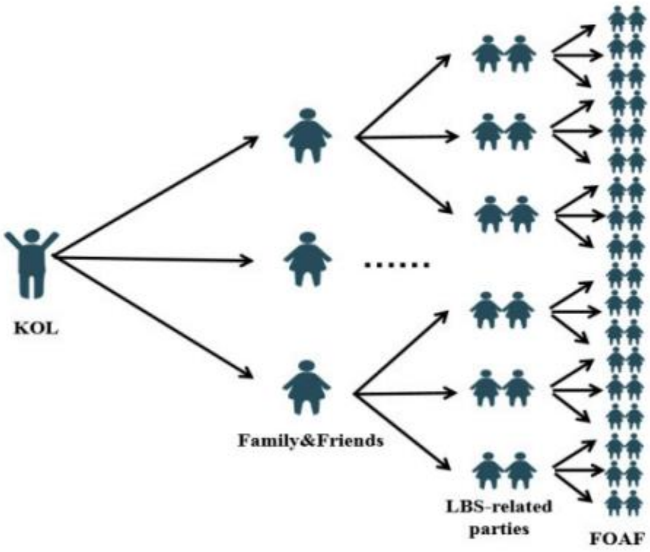

Figure 5.4 The way of social communication of commodity information on the platform [44]

Consumer behavior affects the performance of information dissemination in social commerce networks. Consumer behavior in social commerce includes pre-purchase and post-purchase behaviors, and user suggestions from the same social community have a significant impact on pre-purchase behavior [45]. Based on social media such as WeChat for product distribution, Pinduoduo makes full use of the convenience of interpersonal relationships by using incentive strategies to encourage individuals to promote their products in their circle of friends, thus achieving the effect of attracting more users to join. Using this feature, the platform is not only able to reduce the average customer cost and therefore the price of the product, but also makes it easy for consumers to use the platform. Consumers can simply click on the product links sent by their acquaintances and purchase the products directly without the need for a tedious search and manipulation process.

5.2.2 Purchase behavior

We base our data on the consumer purchase path under 5A theory for the sample.

Table 5.10 Purchase behavior on Pinduoduo

5A	Question	Yes	No
Aware	1.Were you aware the products information on Pinduoduo because of social media advertisement or social recommendation?	269 (89.7%)	31 (10.3%)
Appeal	2.Were you attracted by the products on Pinduoduo because of social media advertisement or social recommendation?	274 (91.3%)	26 (8.7%)
Ask	3.Did you interact with other members on Pinduoduo or take the initiative to search and inquire about the products you were interested in?	273 (91.0%)	27 (9.0%)
Act	4.Did you purchase a product on Pinduoduo?	300 (100%)	0
Advocate	5. Did you share product-related information, such as reviews, recommendations, user experiences, or complaints, with other members on Pinduoduo after receiving products you had ordered?	236 (78.7%)	64 (21.3%)

Aware: From Q1, 89.7% of the sample chose "yes", indicating that nearly 90% of the sample noticed the product information on PDD, such as through media advertisement or system advertisement push.

Appeal: From Q2, 91.3% of the samples chose "yes", which means that more than 90% of the samples were attracted by the product recommendation on PDD, such as through friends' recommendation or social media influencer/KOL recommendation.

Ask: As shown in Q3, 91.0% of the sample chose "yes", indicating that more than 90% of the sample actively searched or asked for products they were interested in on PDD, or interacted with members of the platform.

Act: From Q4, 100% of the sample chose "yes", which means that all of them have purchased products on PDD.

Advocate: From Q5, 78.7% of the sample chose "yes", indicating that nearly 80% of the sample had shared information about the product with others, such as product reviews, recommendations, user experience or complaints, after receiving the ordered product.

In summary, all of the random survey samples had purchase experience on the PDD platform, and the values showed a distribution of Act>Appeal>Ask>Aware>Advocate. We found that this is different from the traditional numerical logic that should be presented by the purchase path of 5A consumers, and shows new characteristics.

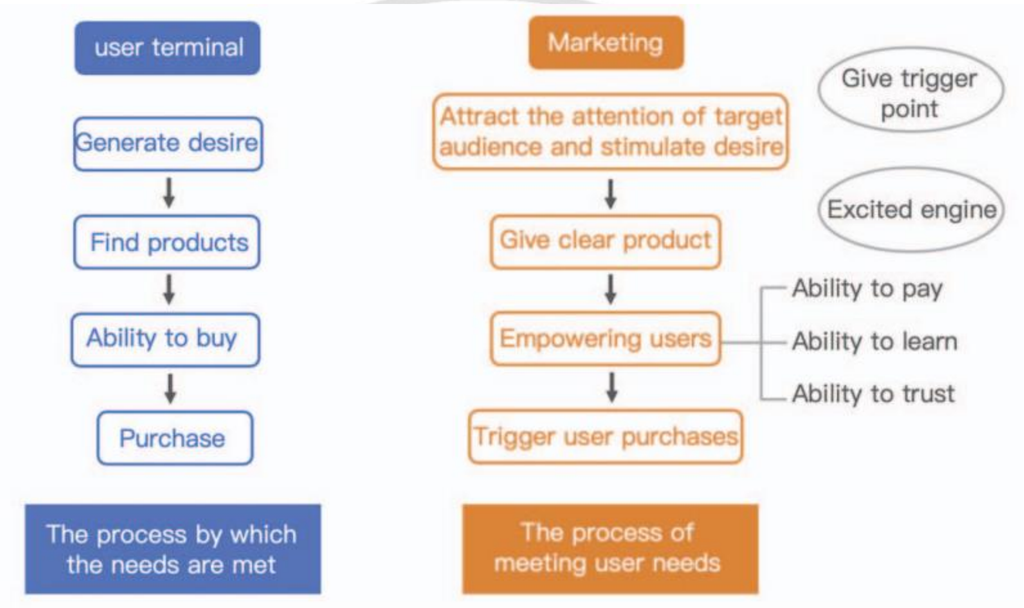

Figure 5.5 Pinduoduo stimulates purchase logic [47]

Pinduoduo's purchasing logic to stimulate consumption is "Consumption drives consumption". Unlike traditional e-commerce seeks people, PDD gathers people, focuses on teamwork and pays attention to timeliness by meeting the consumption range When pricing and meet the product group and the lowest price on the entire network to promote consumers' instant shopping behavior.

We believe that this purchase logic of Pinduoduo stimulates consumption can partially explain why the Act ratio is greater than the other four ratios. Target consumers are triggered to buy after receiving product information and thus adopt the instant shopping behavior, or the products on the information page are daily needed products and they will buy as long as the price is within the accept range. Therefore, they may not need to go through the traditional stage from Aware to Act. In our opinion, social commerce, facilitated by social media and social networking platforms, has stimulated a growth in new business models for e-commerce, enabling the digitization of consumer decision-making processes to trigger new features of purchasing behavior.

We wish to integrate theory with practice, and since social learning constructed by learning from forums and communities (LFC), learning from ratings and reviews (LRR), and learning from social recommendations (LSR), learning is an important predictor of consumer purchase behavior, and since social learning is the only independent variable in the model according to the theoretical structure model of this paper, we conducted the following frequency statistics analysis on the social learning behavior data in our sample.

Table 5.11 Frequency of social learning

Variable	Category	Frequency	Percentage (%)	Mean	SD
Frequency of communities and forums	Never	0	0	5.02	1.35
	Once a month	0	0		
	Twice a month	48	16		
	Once a week	72	24		
	Twice a week	60	20		
	Once a day	66	22		
	Above once a day	54	18		
Frequency of ratings and reviews	Never	0	0	5.26	1.11
	Once a month	0	0		
	Twice a month	30	10		
	Once a week	30	10		
	Twice a week	108	36		
	Once a day	96	32		
	Above once a day	36	12		

Table 5.11 Frequency of social learning (continued)

Variable	Category	Frequency	Percentage (%)	Mean	SD
Frequency of social recommendations	Never	0	0	5.16	1.07
	Once a month	0	0		
	Twice a month	12	4		
	Once a week	78	26		
	Twice a week	96	32		
	Once a day	78	26		
	Above once a day	36	12		
	Total	300	100		

From the above table, the frequency of Learning from forums and communities (LFC) is mainly Once a week, accounting for 24%, followed by Once a day, accounting for 22%. The frequency of Learning from ratings and reviews (LRR) is mainly Twice a week, accounting for 36%, followed by Once a day, accounting for 32%. The frequency of Learning from social recommendations (LSR) is mainly Twice a week, accounting for 32%, followed by Once a week and Once a day, both accounting for 26%.

In summary, learning from ratings and reviews (LRR), twice a week, has the highest frequency in social learning.

Table 5.12 Time of social learning

Variable	Category	Frequency	Percentage (%)	Mean	SD
Time of communities and forums	Never	60	20	2.52	1.08
	Within 15min	84	28		
	Within 30min	108	36		
	Within 1h	42	14		
	Within 3h	0	0		
	Within 5h	6	2		
	Above 5h	0	0		

Table 5.12 Time of social learning (continued)

Variable	Category	Frequency	Percentage (%)	Mean	SD
Time of ratings and reviews	Never	60	20	2.66	1.26
	Within 15min	90	30		
	Within 30min	72	24		
	Within 1h	54	18		
	Within 3h	18	6		
	Within 5h	6	2		
	Above 5h	0	0		
Time of social recommendations	Never	84	28	2.68	1.34
	Within 15min	48	16		
	Within 30min	72	24		
	Within 1h	78	26		
	Within 3h	12	4		
	Within 5h	6	2		
	Above 5h	0	0		
	Total	300	100		

From the above table, Learning from forums and communities (LFC) is mainly Within 30 minutes, accounting for 36%, followed by Within 15 minutes, accounting for 28%. Learning from ratings and reviews (LRR) is mainly Within 15 minutes (30%), followed by Within 30 minutes (24%). Learning from social recommendations (LSR) is mainly Never, accounting for 28% of the time, followed by Within 1 hour, accounting for 26%.

In summary, learning from forums and communities (LFC), within 30 minutes, is the highest in social learning time.

Therefore, in the sample of consumers who made a successful purchase, we conclude this statistic: consumers spend no more than 30 minutes in forums and communities before purchasing a product, and the frequency of checking ratings and reviews is twice a week. This is also consistent with consumers' instant shopping behavior on PDD.

5.2.3 Summary

We believe that experiments can be understood in specific cases and experimental results can guide practice, so we combine Philip Kotler's 5A Customer Behavior Path theory and different types of consumer buying behavior to statistically analyze the questions involving actual buying behavior in 300 valid sample questionnaires obtained under WeChat social platforms. We first conducted frequency statistics and variance analysis of consumers' purchasing behavior on Chinese social e-commerce platforms, and then used Pinduoduo, a well-known Chinese social e-commerce platform, as a case study. The statistical analysis results show that consumers are relatively satisfied with all the measures in the structural model, proving that social learning and social support do facilitate consumers' social interactions, social e-commerce intentions and actual purchase behaviors. Our statistical results also output a consumer profile, which we believe can help guide the improvement of business models, product marketing, and business strategies for social e-commerce platforms.

Table 5.13 Consumer persona

Category	Features
Gender	Female
Age	26-30
Education Level	Bachelor
Occupation	Enterprise staff
Income	Below 5000
City	Guangzhou
Platform	Wechat
Purchase behavior	Variety seeking behavior
Use of frequency	More than once a day
Learning from ratings and reviews (LRR)	Twice a week

Learning from forums and communities (LFC)	Within 30 minutes
Opinions on SL, SS, SCI, PB	Relative agree

CHAPTER 6

CONCLUSIONS AND FUTURE WORKS

6.1 Discussion and implications

The social commerce formations can be divided into two categories. Inclusion of commercial features in social networking sites is one type of formation, and the nature of this form reveals a key element of social commerce, which is consumer-generated content. Content generated by consumers can help consumers make more informed buying decisions, while content provided by companies can help companies achieve their marketing goals. E-commerce sites that integrate social media into their operations are another solution. Through integrated social media features, consumers can create and exchange product-related information with other consumers on e-commerce websites and social networking sites. Creating social media features for e-commerce encourages social commerce behavior as well as reflecting the impact of social media features on consumer buying behavior in the e-commerce environment.

Social learning theory suggests that, during the pre-purchase phase of social commerce, consumers learn basic pre-purchase information through social learning and acquire social support from existing users of social media platforms, which ultimately influences consumers' purchasing intentions and makes purchase decisions [17]. Consumers can access useful information through social commerce in a variety of ways, which is helpful for them when making purchase decisions. In order to assist in product evaluation and purchase decisions, customer ratings and reviews provide independent reviews of products from other customers. Through social media such as Wechat, consumers can share product links, consumer information, and shopping experiences, as well as provide advice and recommendations during the buying process while building good social relationships. Consumers' social experiences and interactions are enhanced when personal shopping-related information is exchanged [46]. This provides social support among customers to improve their purchase decisions when shopping online.

The throughput and factor analysis of this study were carried out using structural equation modeling (SEM), and the model demonstrated good reliability and validity. As for testing the hypotheses, the partial least squares (SEM-PLS) method was used. In this study, we analyzed the relationship between social support and social learning with regard to social commerce intention and consumer behavior. The results indicate that social learning has a positive impact on social support, social commerce intention, and consumer purchase behavior, but it has indirect rather than direct effects on purchase behaviors. Additionally, social support affects social commerce intentions, while social support and social commerce intentions affect purchase behavior. These results are consistent with previous studies. For example, [9] and [42] also demonstrated the effect of social learning and social support on purchase intention and decision making. However, their studies only stopped at the relationship between social learning, social support and purchase intention, and did not further investigate their relationship with purchase behavior. Although purchase intention is an important indicator of customers' purchasing behavior, purchase intention is not equivalent to actual purchasing behavior. In contrast, the structural model constructed in this study demonstrates the relationship between social learning and social support with social e-commerce intention and purchase behavior, and points out that social learning is related to purchase behavior through social support and social commerce intention, and this relationship is positive, indirect, and significantly affects the relationship. It is also demonstrated that social learning, social support, and social commerce intention are important indicators of purchase behavior and can predict consumers' purchase behavior.

Meanwhile, we use Pinduoduo, a well-known social e-commerce platform in China, as a case study. We hope to make a specific study of consumer behavior with the case study to verify the consistency between our theoretical analysis results and actual consumer behavior. We combined Philip Kotler's 5A customer behavior path theory and different types of consumer buying behaviors to conduct frequency analysis and variance analysis on 300 valid sample questionnaires obtained under WeChat social platform by SPSS statistical method. The results of the statistical analysis show that consumers do not show significant differences between social learning and social support and social commerce intention and purchase behavior, and are relatively satisfied with all the measures in the structural model, proving that social learning and social support do promote consumers' social interaction, social e-commerce intention and actual purchase behavior. Our statistics also output a consumer profile, which we believe can help guide the improvement of business models, product marketing, and business strategies for social commerce platforms.

Recommendations:

This research has led to a shift in research on social e-commerce to the social aspect rather than the e-commerce aspect. The theoretical model we propose will drive further development of research on consumer purchase behavior. In addition, we output a consumer profile, which we believe can help guide the improvement of business models, product marketing, and business strategies for social e-commerce platforms. More important, it promotes the development of social commerce industry.

1. Theoretical Contributions

The present study has several contributions to the theoretical part as follows.

First, this study extends the application of social learning theory and social support theory. Although social learning theory and social support theory originate from social psychology, they nowadays have a considerable impact on social business contexts. Learning from forums and communities, learning from ratings and reviews, and learning from social recommendations have not only changed consumers' social patterns, but also improved the quality of their decisions.

Second, this study highlights the different roles of different social business structures. In the social commerce environment, various social features are designed, but they play different roles and have different impacts on consumers' purchasing behavior, so investigating different social commerce structures and comparing them to understand their different roles will not only give us a comprehensive understanding of social commerce, but also help us focus future research on the more influential parts.

Third, this study extends the application of 5A customer behavior path theory. The new e-commerce purchasing behavior presents different characteristics than before according to the development of the Internet, for example, consumers have to observe the behavior of others and the interaction between the environment and behavior, which prompted the need for research on the characteristics of consumer online purchasing behavior to also keep up with the times, which will benefit the development of consumer behavior theory research.

2. Practical Implications

The present study has several contributions to the practical part as follows.

First, it can help managers of social commerce sites to better understand customers' buying behavior and decision-making patterns and to design a rational site structure. Although learning from ratings and reviews and learning from social recommendations cannot have a direct impact on consumers' purchasing behavior, they can indirectly improve the quality of customers' decisions, thus increasing customer satisfaction and guiding the generation of consumer purchasing behavior.

Second, it can help different social commerce platforms to develop appropriate product positioning and advertising and marketing strategies. For example, consumers on PDD platforms are more cost-conscious and mainly buy low-priced products, and tend to buy similar products from different brands, so promotions then play an important role in increasing consumers' purchasing behavior.

Third, it helps to improve the business model of social commerce. Although website quality and providing consumers with a good user experience have a positive impact on improving the quality of consumers' purchasing decisions, in addition to e-commerce platform optimization, social factors also play an important role in the development of the social e-commerce industry, so promoting consumers' social interaction behavior from various aspects is also something that social e-commerce practitioners need to focus on.

Table 6.1 Practical implications

Categories	Findings	Practical implications
Structural model	SL is not correlated with PB, but positively correlated with PB by SS and SCI	Make it easier for customers to identify their needs and increase the number of resources on forums and communities
	SL, SS, SCI are important indicators of PB and can predict PB.	Drive consumer buying behavior based on social commerce structures
	The sample's view on SL, SS, SCI, PB is mainly Relative agree	Develop improvement programs based on consumer-generated content in social commerce platforms
S-commerce platform	Mainly use Wechat, followed by PDD, Weibo	Develop product placement and business strategies based on the social commerce platforms used by consumers
5A customer behavior path	Consumer purchase decision process presents new characteristics	Develop business models based on consumer purchase decision processes
Type of purchase behavior	Mainly Variety seeking behavior	Develop product pricing, brand positioning and marketing strategies based on the type of consumer buying behavior
PDD case study	Consumer portrait	Based on consumer profiles, merchants can quickly find target users and develop appropriate product design and sales promotion methods

In our view, the major contributions of this study are:

(1) We have specifically analyzed consumer purchase behavior in the social business environment through both 5A consumer purchase paths as well as purchase behavior types, which will enable us to better understand the characteristics of consumer behavior and the customer purchase decision process under this emerging phenomenon.

(2) By verifying that social learning and social support can positively influence consumer purchase intentions and decision processes, this study expands the wide application of social learning and social support theories in the fields of psychology and sociology, and contributes to the growing body of literature on social commerce.

(3) Social commerce operators will be able to use the findings to optimize the structure of social commerce and allocate resources rationally; and marketers will be able to enhance the shopping experience of online consumers, making marketing activities more effective and successful.

6.2 Limitations and future works

We acknowledge the limitations of this study. First, the sample size was not very large. Although the PLS-SEM method we used is a component-based approach with minimal sample size requirements and good reliability and validity to support all hypotheses in this study, larger sample sizes and other analytical methods can be used in future studies to test causal relationships in our model. Second, the sample was not wide enough, coming from only one province in China (Guangdong). Although Guangdong Province is one of the top three economically developed regions in China, and the social commerce industry is relatively leading here, as in most empirical studies, the scope of the survey respondents poses some limitations on the generalization of the results. Since purchasing behavior can be influenced by different cultural and geographical contexts, generalizing findings to other contexts should be done with caution, while future studies could incorporate generational or urban-rural differences. Finally, this study used WeChat as a sample data collection tool. Although WeChat is the most widely used social network in China, we collected data from specific social networking sites, which may still have its limitations.

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