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The power of social learning: How do observational and word-of-mouth learning influence online consumer decision processes?

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ABSTRACT

Observational learning (OL) and word-of-mouth learning (WOML), two main types of social learning, can influence online consumer decisions. The consumer decision process is not limited to consumption decisions; it may be viewed as a problem-solving process that includes three stages: search, evaluation, and purchase. To date, the effects and the mechanisms of OL and WOML on the purchase process remain unclear for both researchers and marketers. In this study, we examined the differences between the effects of OL and WOML on consumers' decisions at three online shopping stages through the theoretical route of motivation reinforcement. This approach revealed the influencing mechanisms, and we further investigated the moderating role of product involvement. We found that WOML has a greater influence on the consumer decision process than OL when consumers purchase high-involvement products, while OL has a greater influence on the consumer decision process than WOML when consumers purchase low-involvement products. Furthermore, OL will reinforce consumers' extrinsic motivations, while WOML will reinforce consumers' intrinsic motivations, which are negatively moderated by product involvement and sequentially affect the consumer decision process. This study enhances the theoretical understanding of the effects and mechanisms of social learning on the consumer decision process. Our findings provide meaningful insights for platform managers and sellers on how to effectively assist consumers from the beginning to the end of the purchase process.

1. Introduction

Online consumers tend to collect information to assist consumption decisions (Huang & Benyoucef, 2013) by adopting social learning (SL) methods (Bandura, 1977; Cheung, Liu, & Lee, 2015). One traditional SL method is observational learning (OL) (Bandura & McClelland, 1977; Bikhchandani, Hirshleifer, & Welch, 1998). Consumers can observe the actions of others and then determine how to adopt new behaviors. They can later utilize this information to guide their future actions and avoid unnecessary mistakes in the process of online shopping decision making (Z. Shi & Whinston, 2013). Another SL method is word-of-mouth learning (WOML). Consumers can learn from and be affected by other consumers' opinions (Arndt, 1967). In practice, online sellers and platform

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managers have realized the crucial roles of OL and WOML in sales. Online platforms have developed some advanced IT tools to facilitate consumers' OL and WOM by providing historical sales and online reviews.

Both platform managers and online sellers need to understand whether facilitating WOML, OL, or both simultaneously will be more effective in influencing consumers' decisions. Because platform managers have to weigh which information should be provided on a limited webpage or whether to develop new IT tools. Sellers must overcome new challenges since managing information to facilitate WOML and OL often requires separate strategies to manage costs and pursue economic utility.

It is still unclear whether OL or WOML is more effective in assisting consumers' decisions. Although several studies have measured their effects (Gilal, Zhang, Gilal, & Gilal, 2019; Godes & Mayzlin, 2004; Hanson & Putler, 1996; Herhausen, Ludwig, Grewal, Wulf, & Schoegel, 2019; Xinxin Li, Hitt, & Zhang, 2011; Liu, 2006; Nakayama & Wan, 2021; Salganik, Dodds, & Watts, 2006; Soltysinski & Dholakia, 2001; J. Zhang, 2010; Zhuang, Cui, & Peng, 2018), only a few studies have argued their differences on consumers' purchase decisions (Y. Chen, Wang, & Xie, 2011; Cheung, Xiao, & Liu, 2014; Xitong Li & Wu, 2013). In addition, prior studies have tended to treat consumers' payment intentions or consumption decisions as the ultimate outcomes of their model (X. Shi, Zheng, & Yang, 2020), particularly when exploring how social learning affects consumers' final purchase decisions (Y. Chen et al., 2011; Cheung et al., 2014; Xitong Li & Wu, 2013).

However, most consumers often search for product information, evaluate products sold by different sellers, and even add products to their shopping carts, but do not make a purchase decision immediately or ultimately. Thus, most consumer purchase decisions are not disconnected actions but are complex processes, which can be considered problem-solving processes that include different stages (Engel, Blackwell, & Minniard, 1993; Masterson & Pickton, 2010). In practice, frequent interactions in virtual environments may not increase the probability of an eventual sale (Y. Wang & Yu, 2017), but few studies have considered the online consumer decision process as the outcome of research models addressing the effect of social learning on consumers' decisions. Furthermore, if there is a difference between the effects of OL and WOML on the online consumer decision process, the reason remains poorly understood. In summation, few studies have considered the differences between the effects of OL and WOML on the consumer decision process and their influential mechanisms.

Online consumers' decisions will also be moderated by some additional factors. For example, when purchasing products of different involvement levels, consumers perceive different correlations (Hong, 2015), and they might exert different weights to learn via OL or WOML. For instance, when purchasing high-involvement products, consumers might collect more information and actively participate in discussions on these products. However, the moderating role of product involvement on the relationship between OL or WOML and online consumers' decision processes remains unclear.

Therefore, in this paper we explore the power of social learning, specifically how OL and WOML influence the online consumer decision process. We also investigate their mechanisms. We seek to answer the following research questions:

Q1: Do OL and WOML have significant and differential effects on online consumers' decision processes, and if so, what are these effects?
Q2: What is the influencing mechanism of OL or WOML on online consumers' decision processes? In other words, what is the mediation factor between OL or WOML and online consumers' decision processes?
Q3: Does product involvement moderate the role of OL or WOML on online consumers' decision processes, and if so, how is this moderation effected?

To answer the above research questions, we consider three stages in the online shopping process: "product search," "product selection and evaluation," and "final purchase decision" (Engel et al., 1993). We have conducted two separate studies as follows. Study 1 is a pilot study using behavior experiments to explore the significant and differential effects of OL and WOML on the consumer decision process and the moderating role of product involvement. Specifically, we have built an experimental platform for online shopping on which participants could fulfill shopping tasks via OL and WOML separately. Study 2 is a structural equation modeling analysis to confirm the main effect and further reveal the influence mechanisms of OL and WOML on the three online shopping stages. It also explores the moderating effect of product involvement based on motivation reinforcement theory.

This study provides several theoretical and practical contributions. First, to the best of our knowledge, our research is one of the first to explore and compare the different effects of OL and WOML on the three stages of online consumer decision making, which enriches the literature that discusses the power of online social learning on the online consumers' decision processes. Second, although prior studies have drawn on various information theories, such as signal theory (Cheung et al., 2014) and information cascade theory (Y. Wang & Yu, 2017), this study introduces the motivation reinforcement theory from the perspective of social psychology to better understand the impact of OL and WOML on online consumers' decision processes. Third, this study creatively investigates the moderating role of product involvement on the relationships between OL or WOML and consumers' decision processes, and further explores the moderating role of product involvement on the relationships between OL or WOML and consumers' motivations. Furthermore, the results of our research can offer a theoretical basis for sellers and platform managers to fully utilize to the power of social learning and so provide better shopping-related information to improve the convenience and efficiencies of the online consumer's shopping experience.

This paper proceeds as follows: Section 2 provides the theoretical background. Section 3 develops the hypothesis. Section 4 describes the research methodology and presents the results of studies 1 and 2. Section 5 demonstrates our main findings and discusses the implications for management scholars and practitioners. Finally, Section 6 discusses the limitations and directions for future research.

2. Theoretical background

2.1. The consumer decision process

Most consumer purchase decisions are not a disconnected action but a complex process, which can be considered a problem-solving process that includes either three stages (i.e., search, evaluation, and purchase) (Engel et al., 1993) or five stages (i.e., need recognition, information search, evaluation of alternatives, purchase decision, post-purchase behavior) (Masterson & Pickton, 2010). Previous studies have attempted to integrate the various stages of the decision-making process (William B Dodds & Monroe, 1985; Mobley, Bearden, & Teel, 1988), or have focused on a specific stage rather than several stages of the process as follows.

First, at the search stage of the consumer decision process, consumers exert varying degrees of energy to seek out and process information as they learn about available products (Teo & Yeong, 2003). Sridhar, Ratchford, and Talukdar (1997) presented a theoretical model that identifies not only what factors affect consumers' search behavior but also how these factors interact with one other. Moreover, at the search stage, social media campaigns are of great importance to consumer decisions (Tussyadiah & Fesenmaier, 2009).

Second, at the evaluation stage of the consumer decision process, consumers' connections to marketers and other sources of information are much more likely to influence their ensuing choices than marketers' efforts to persuade them (Hudson & Thal, 2013). Prior literature has explored the effects of various factors on the evaluation stage, such as online brand communities (R. P. Bagozzi & Dholakia, 2006), price (William B Dodds & Monroe, 1985), store information (W. B. Dodds, Monroe, & Grewal, 1991).

Third, at the purchase stage of the consumer decision process, Dhruv, Jerry, and Howard (1994) underscore the important impact of the perceived risk associated with the purchase. Novices are more likely to rely on WOM and OL information than experts at this final stage of the decision process (Alba & Hutchinson, 1987).

However, few studies have comprehensively investigated the different effects of OL and WOML on the consumer decision process from the first stage to the final stage, which is important to both researchers and marketers.

2.2. Social learning

The term "social learning" was coined by Bandura (1977) based on the work of psychologist Kurt Lewin, referring to an individual learning process that revolves around and relies on social interaction (Webler, 2005). Bandura (1977) argued that social learning is a personal learning process that depends on social interaction. Webler (2005) argued that in sociology, social learning is no longer a learning process for individuals in social environments, and it may be the result of people's cognitive coordination and normative adaptation in social change. In the field of marketing, social learning has been applied to study the market behavior of economic individuals, such as consumers or enterprises. Consumers consider the information selected by others to be more important than what they have collected, so social learning is an effective tool for transferring information from existing to potential consumers (Ilfeld, 2004; Joo, 2008).

Çelen, Kariv, and Schotter (2010) suggested that social learning helps to describe scenes in which people observe other individuals' behaviors. This learning method not only includes observing behaviors, but also searching for others' suggestions. According to Joo (2008), social learning is a process that delivers the experience and information of existing customers to potential customers in the two following ways: a) consumers observe others' purchase choices, also known as OL, or b) they obtain direct advice from experienced consumers in the market, namely, WOML (Çelen et al., 2010; Joo, 2008).

2.2.1. Observational learning

Bandura (1977) argued that observing others' choices and obtaining information influences individuals' behaviors. OL affects consumers' purchase decisions. Informational cascades (Bikhchandani, Hirshleifer, & Welch, 1992) explain the mechanism of OL, and it can be of interest to highlight this phenomenon in online shopping. The weight of the observed purchase behavior of all previous buyers is far greater than that of consumers' knowledge when they are making purchase decisions because of the scarcity of available information (Bikhchandani et al., 1992). Numerous studies have repeatedly proven that OL influences the result of consumer purchase decisions. Some have tested the influence via laboratory studies (Anderson, Goeree, & Holt, 2002; Çelen & Kariv, 2004), whereas others have illustrated the effects through field tests (Cai, Chen, & Fang, 2009; Y. Chen et al., 2011; J. Zhang, 2010).

2.2.2. Word-of-mouth learning

WOML is regarded as the type of information conveyed by consumers about a particular brand, manufacturer, or seller, and the associations of these with any organization or individual. Thus, it is a two-way, interactive communication approach that changes others' attitudes in varied contexts, such as patients' online health behavior (S. Chen, Guo, Wu, & Ju, 2020; X. Zhang, Guo, Xu, & Li, 2020), users' sample downloading behavior (Shengli & Fan, 2019) or consumers' shopping behaviors (Arndt, 1967; Wangenheim, 2005). Traditionally, the spread of WOML often relies on friends and surrounding people; however, the influence of online WOML arose with the popularity of the Internet and instantaneously broke all traditional limitations, such as time, space, and social distance. WOML comprises both positive and negative reviews generated by actual and potential customers of a product, a brand or a company, and these comments can be widely spread online. Electronic WOML has a series of characteristics, including high speed, a wide range of transmission, large amounts of information, storability, instant receipt, anonymity, and time-space freedom (Hennig-Thurau & Thorsten, 2004). These characteristics enable people to adopt WOML through the Internet. Consumers tend to search for comments before shopping online to the risk associated with their purchase (Bansal & Voyer, 2000; Hao, Zou, & Li, 2012; Maru File, Cermak, &

Alan Prince, 1994).

2.2.3. Difference between impacts of OL and WOML

Although some studies have measured the effect of OL or WOML (Chevalier & Mayzlin, 2006; Gilal et al., 2019; Godes & Mayzlin, 2004; Hanson & Putler, 1996; Xinxin Li et al., 2011; Liu, 2006; Salganik et al., 2006; Soltysinski & Dholakia, 2001; J. Zhang, 2010; Zhuang et al., 2018), few studies have measured the effects of OL and WOML while discussing their differences (Y. Chen et al., 2011; Cheung et al., 2014; Xitong Li & Wu, 2013; Y. Wang & Yu, 2017). Y. Chen et al. (2011) conducted three longitudinal, quasi-experimental field studies to examine the differential impacts of OL and WOML on product sales by using data from online sellers on the online retail site Amazon.com. They focused on the valence of electronic word of mouth (WOM) and OL and found that negative word of mouth is more influential than positive word of mouth; moreover, positive OL information significantly increases sales, whereas negative OL information has no effect. Xitong Li and Wu (2013) found that both OL and WOML can positively increase sales, and the effect of WOML mediated via Facebook is larger than that of OL. Cheung et al. (2014) collected data from a popular online beauty community and found that OL information is more influential on consumer purchase decisions than WOML; this effect is moderated positively by consumer engagement and negatively by consumer expertise. Y. Wang and Yu (2017) conducted a survey to examine the impact of OL and WOML on consumer purchase intention and actual purchase behavior. They found that positive and negative WOM, WOM content, and OL significantly affect consumers' intention to buy a product, increasing the likelihood of buying and sharing product information with others on social commerce sites.

2.3. Motivation reinforcement

The theory of motivation reinforcement was derived from the long-term observation of the animal learning process [69]. Reinforcement theory then developed rapidly in cybernetics, statistics, psychology, neuroscience, and computer science (Kaelbling, Littman, & Moore, 1996). In the exploration of reinforcement theory in psychology, an animal receives one external stimulus or experiences the disappearance of one stimulus, and the correlation pattern between behavior and another stimulus or response is reinforced in intensity and frequency. Neural network scientists (Bush & Mosteller, 1955; Widrow & Hoff, 1960) and psychologists (Bush & Mosteller, 1955) have studied reinforcement theory. However, they have mainly focused on "rewards" and "punishment." With the continuous progress of artificial neural network research and computer technology, research on reinforcement learning has come to a climax and gradually become an active field in machine learning research (Holroyd & Coles, 2002; Mnih et al., 2015; Sutton & Barto, 2005). The reinforcement theory of task motivation has assumed that the effects of extrinsic and intrinsic reinforcement are additive in nature (Hamner & Foster, 1975).

In the academic field of motivation theory, researchers have consistently distinguished between extrinsic and intrinsic motivations to drive an activity (Deci & Ryan, 1985, 2010). Both types of motivation are influential predictors of online shopping (Shang, Chen, & Shen, 2005). Extrinsic motivation means that the individual's motivational stimulus comes from outside (Ryan & Deci, 2000). Intrinsic motivation means that the individual's motivational stimuli come from within, such as curiosity or social contact (Ryan & Deci, 2000).

2.4. Product involvement

Product involvement refers to product and personal correlations perceived by consumers based on their demands, interests, and values (Griffith, Krampf, & Palmer, 2001; Krugman, 1965; Zaichkowsky, 1985, 1994). If consumers perceive high personal correlations in certain products, they will collect more information and actively participate in discussions about these products. Thus, these products become high-involvement products, entailing a higher perceived risk and a stronger trust expectation (Hong, 2015). Recent research on consumer behavior and social psychology has focused on the way in which involvement moderates the amount and type of information processing elicited by persuasive communication (Petty, Cacioppo, & Schumann, 1983). The elaboration likelihood model (ELM) (Petty et al., 1983) clarifies the level of reflection on relative arguments embedded in the information (Fan, Han, & Sun, 2013), revealing the differences between high- and low-involvement products in aspects like information processing. Product involvement affects consumers' efforts in information searching and their evaluation patterns for product quality and performance, ultimately influencing consumers' purchase decisions (Beharrell & Denison, 1995). Therefore, in our research context, consumers may exert different weights to learn via OL or WOML when purchasing products that differ in their level of involvement. That is, product involvement is a reasonable moderating variable in research that explores social learning and consumer decision making.

3. Hypothesis development

3.1. Consumer decision efficiency

In this research context, we take consumer decision efficiency of the online shopping process (i.e., search, evaluation, and purchase) as a dependent variable. The concept of efficiency is fundamental to economics and summarizes the notion of obtaining the largest possible output, given the available technology and constraints, from a set of inputs (Sproles, Geistfeld, & Badenhop, 1978). In a general sense, efficiency is the (often measurable) ability to avoid wasting materials, energy, efforts, money, and time in doing something or in producing a desired result. It often specifically comprises the capability of a specific application of effort to produce a specific outcome with a minimum amount or quantity of waste, expense, or unnecessary effort (Sickles & Zelenyuk, 2019). When applied in the context of consumer purchase decision-making, the efficiency of consumer decision making refers to the degree to which a consumer obtains the greatest possible utility or satisfaction from a consumption decision, given a fixed set of resources allocated to the decision (Sproles, Geistfeld, & Badenhop, 1980). In this paper, following prior research (Kao, 2017), we measure consumer decision efficiency based on four aspects: effort, time, energy, and satisfaction.

3.2. Social learning

When people try to meet satisfy their needs driven by a certain purchase motivation, their purchase decisions consist of the process of analyzing, evaluating, selecting, and implementing the best purchase decisions out of two or more alternatives (Engel et al., 1993). The process of consumers' cognitive learning and selection of commodities mainly includes such information as the cognition of product parameters, the judgment of quality, and agreement with the requirements of the purchase. These are all directly related to consumers' online shopping decisions. In the decision-making process, consumers adopt cognitive learning and information processing through different approaches to social learning; then, they integrate the information into a more complex point of view, and finally, they exhibit behavioral responses based on motivation. Consequently, we propose the following:

H1. : Social learning has a significant positive and differential influence on the decision efficiency of the online shopping process.

OL and WOML are the two major methods of social learning [27]. If decision makers observe many consumers buying a certain product, they will naturally assume it is of high quality and tend to follow the choice of their companions; this accordingly affects their decision-making process. In situations of information limitedness or overload, consumers may observe the behaviors of previous buyers and refer to or follow their predecessors' actions, enforcing the effect of learning and finally allowing them to make purchase decisions in conformity with the majority (Anderson et al., 2002; Çelen & Kariv, 2004). Since OL can affect the results of consumers' decision making, it can provide consumers with new information, change the efficiency of product search, product selection and evaluation, and purchase decisions, ultimately affecting the efficiency of the online shopping process and its results. Many studies on WOML have proved its influence on several aspects of shopping, such as consumers' purchase intention, the possibility to buy (Vázquez-Casielles, Suárez-Álvarez, & del Río-Lanza, 2013), and product output (Y. Chen et al., 2011; Cui, Lui, & Guo, 2012). The influence of WOML on the consumer's online shopping decision process appears at each stage (Bansal & Voyer, 2000). Therefore, we propose the following:

H1a. : Both OL and WOML have significant positive influences on the efficiency of the online shopping process.

Consumers use different weighing methods for different degrees of product involvement. Consequently, for online products with different degrees of involvement, the extent of the influence exerted by social learning will differ at each stage of online shopping decision making. Differences in information needs related to products with different degrees of involvement in online shopping will lead to distinct consumer online shopping decisions (Burnkrant & Sawyer, 1983; Eisend, 2007; Park, Lee, & Han, 2007). Specifically, there are two paths related to such decisions—a central path and a peripheral path. High-involvement products generally use the central path, while low-involvement products take the peripheral path. Shopping for high-involvement products is more complicated for consumers, so they are more patient and careful, increasingly elaborating on meanings during the comprehension stage of information processing. In contrast, shopping for low-involvement products is less complicated for consumers, so they rely on peripheral cues from such stimuli as sales rankings, the pictures included on the product page, and the attractiveness of the pictures (Lee, Park, & Han, 2008). OL content is more intuitive compared with that of WOML. OL only provides the final choice of users, while WOML presents users' reviews and suggestions and explains the reasons for their choices. When purchasing low-involvement products, consumers depend more on the peripheral path (Park et al., 2007).

Consumers tend to simplify the process of collection, evaluation, and comparison. Consequently, comprehensiveness of information does not become a key factor, and consumers require more direct, rapid, and simple information. Compared with WOML information, consumers are more inclined to use OL for purchase decisions. Thus, we propose the following:

H1b. : OL and WOML have significant differential influences on the efficiency of the online shopping process. Specifically, WOML has a greater influence on the online shopping process than OL when consumers purchase high-involvement products, while OL has a greater influence on the online shopping process than WOML when consumers purchase low-involvement products.

3.3. Motivation reinforcement and product involvement

Based on the theory of motivation reinforcement, information from other consumers, such as observational information or WOML, can be regarded as some type of stimulus in this study. Once the consumer receives this stimulus, the motivation to purchase a product will be reinforced; hence, the correlation pattern between consumer behavior and the stimulus will be reinforced. Thus, we propose the following:

H2. : Social learning has a significant positive reinforcement effect on motivation, influencing the decision efficiency of the online shopping process.

Both extrinsic and intrinsic motivations are influential predictors of online shopping (Shang et al., 2005). Extrinsic motivation means that the individual's motivational stimulus comes from outside (Ryan & Deci, 2000). It should be noted that, although the stimuli come from outside, the result of performing the task will still be rewarding for the individual performing the task, as it would be in avoiding punishment (e.g., risk). In the online shopping environment, online consumers can observe the group decision results of other consumers since historic sales can be seen on the webpage. Consumer herd behavior is a common phenomenon for avoiding risks associated with extrinsic motivation. The herding effect occurs when consumers observe other consumer group behaviors, which has been proven by numerous experiments (Allen, 1965; Asch, 1956; Bearden & Etzel, 1982).

Intrinsic motivation means that the individual's motivational stimuli come from within, such as curiosity or social contact (Ryan & Deci, 2000). For example, consumers may be curious about the specific purchase reasons or experiences of a product of prior consumers. These purchase reasons and experiences can be expressed in both positive and negative reviews. Based on cognitive evaluation theory (Ryan & Deci, 2000), feelings of competence, especially when reading positive reviews (supportive information), can catalyze intrinsic motivation. Thus, we propose the following:

H2a. : OL will reinforce consumers' extrinsic motivation, while WOML will reinforce consumers' intrinsic motivation; hence, OL and WOML positively influence the decision efficiency of the online shopping process.

According to the ELM (Petty et al., 1983), when purchasing high-involvement products, consumers have higher motivation to exert cognitive effort, and there is a greater likelihood of more elaborate processing. When selecting high-involvement products, consumers usually collect more information and evaluate and compare alternatives thoroughly to eliminate uncertainty and evaluate their decision-making process (Engel et al., 1993; Gilly, Graham, Wolfinbarger, & Yale, 1998; Hair, Anderson, Tatham, & Black, 1998), so the buying process is more complex (Jin, 2007). When shopping for high-involvement products, consumers will also tend to have more patience and exhibit a greater capacity for collecting and comprehending information from various sources than when shopping for low-involvement products. Consequently, the influence of one kind of social learning decreases with increasing product involvement. As a result, we propose the following:

H2b. : Product involvement has a significant and negative moderating role in the relationship between social learning and motivation reinforcement.

As per the review of the theoretical background and hypothesis development, we construct our research framework as shown in Figure 1.

4. Research methodology

In this paper, we conducted two studies as follows. Study 1 is a pilot study using behavior experiments to explore the significant differential effects of two methods of social learning on the consumer decision processes and the moderating role of product involvement. Study 2 is a structural equation modeling analysis to confirm the findings of study 1 and further reveal influence mechanisms based on motivation reinforcement theory, including a) the mediation factor between social learning and the efficiency of the online shopping processes, and b) the moderating role of product involvement on the above relationships.

4.1. Study 1: behavior experiment

Study 1 aimed to construct an e-commerce shopping platform and adopt behavioral experiments with the following goals: a) to understand the effect of social learning on consumer shopping decisions, b) to compare the differential effects of OL and WOML when purchasing products with different degrees of involvement, and c) to investigate the interaction between social learning and products with different degrees of involvement at different stages of purchasing behavior.

4.1.1. Pilot study and participants

Before finalizing the experimental procedure, we carried out a pilot study to determine the characteristics of our participants. In this pilot study, a total of 150 questionnaires were randomly distributed in the sample database of Sojump, the largest questionnaire website in China, and 143 replies were collected. This pilot study helped discover which websites, seller information, prices, OL, and WOML information were of high concern when consumers shopped online and determine which parameters that consumers cared about were displayed on the webpage and their specific values.

In the main experiment, we recruited 93 volunteers, including 46 men and 47 women, with an average age of 24 years. We randomly created four groups of participants, each composed of 23 or 24 people. We found a relative balance between men and women, who ranged in age from 18 to 30 years. Most were college students with bachelor's or graduate degrees whose online purchase

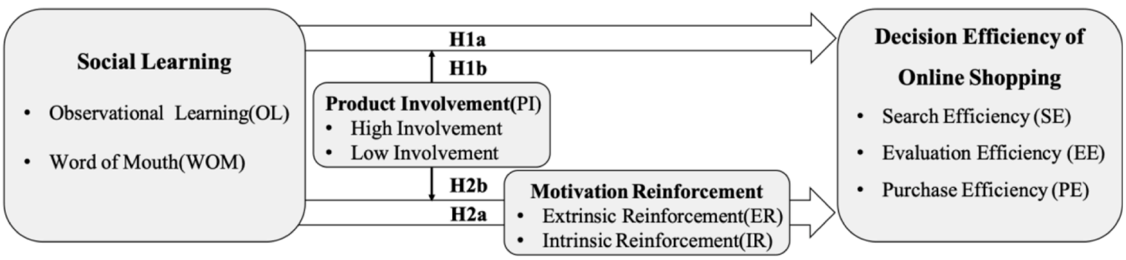

Fig. 1. Research framework.

frequency was mainly once or twice a month or at least once in three months.

4.1.2. *Experiment design and procedure*

4.1.2.1. Experiment design. The tests shown in this study were carried out from June to October 2018, and they took place in the behavior laboratory of Beijing University of Posts and Telecommunications. Except for the operating system, browser, experimental platform, and relative information, the computers used in the experiment had no other content with no connection to the Internet. We controlled tasks on the server side and remained connected to the participants' computers via the wireless local area network. The experiment design included three parts: product selection, experimental materials, and the experiment rating scales. These are described as follows.

Product selection. A panel of eight experts was created to choose appropriate goods for high and low involvement. Alba and Hutchinson (1987) distinguished consumer expertise from product-related experience and considered experts as consumers who are capable of processing a product's attribute information. In this study, the panel of eight experts were consumers who had rich online shopping experiences. With consideration of the popularity of online products and the characteristics of the participants, the panel selected smartphones as the high-involvement product and laundry detergent as the low-involvement product. Smartphones were chosen as the high-involvement product for the following reasons: a) smartphones have become an indispensable product in daily life and buying smartphones online has been widely accepted by consumers; b) the price of smartphones is relatively high, and the purchase decision process is valuable and important. Consumers need to search for more information through various channels to learn about and compare products when making purchasing decisions, such as brand, performance, and price. Laundry detergent was chosen as the low-involvement product for the following reasons: a) laundry detergent is a common daily consumption item and buying laundry detergent online has been widely accepted by consumers; b) the price of laundry detergent is relatively low, and consumers know its functions well. Consumers do not need to spend a lot of time searching for more information when making purchasing decisions.

Experimental materials. Based on the feedback from the pilot research, we took 50% of the total proportion of the above items as experimental materials as follows: a) website information: reputation, brand, and demonstration styles; b) online shop information:

Fig. 2. Experiment materials.

product description, product parameters, and brands; c) price information: product prices and promotion; d) major modes of OL: searching keywords in the product description, such as "hot," "popular," and "popularity," ranking products according to sales volumes or rankings provided by sellers; and e) major modes of WOML: comments on the product page. Our experiment included all of the above information, focused on specific forms of browsing, and sought to strengthen the stimulating effect of different information sources for consumers. We constructed a virtual e-commerce shopping platform, "Tian Tian Hao Huo Mall," which offered a search page and detailed product information page of both high- and low-involvement products (see Figure 2). The search page and detailed information page were shown separately in two controlled trials and four learning experiments to ensure an independent environment and control the interference factors. The learning experiment included one method of social learning (i.e., OL or WOML). We also controlled the website information, product information, and price information in all six experimental groups. For instance, the high involvement*control group, high involvement*OL group, and high involvement*WOML group shared the same information about the website, products, prices, and so on. Only the methods of social learning differed among the above groups.

Experiment rating scale design. The experiment rating scale was an important research factor and included three parts: a) an introduction to the questionnaire and personal information, b) a description of scenarios, and c) an assessment of product search, selection and evaluation, and purchase decisions. In this study, the dependent variable was "efficiency of consumer online shopping decision-making" (i.e., decision-making efficiency at three stages of the consumer's online shopping decision -making process: "search," "evaluating," and "buying"). We employed a 7-point Likert scale (1 = totally disagree, 7 = totally agree). The scale for search efficiency, evaluation efficiency, and purchase efficiency was adapted from Kao (2017) and Engel, Blackwell, and Minniard (1993), with a total of twelve items. For social learning, the scale was derived from an adaptation of work from Awad and Ragowsky (2008), Wang and Haggerty (2011). For product involvement, the scales concerning consumers' costs and efforts were adapted from Zaichkowsky (1994).

4.1.2.2. Experimental procedure. This study used a 3 (social learning: control, OL, and WOML) * 2 (product involvement degree: smartphone and laundry detergent) within-participants experimental design. All participants underwent two controlled experiments and then four learning experiments. The order of undergoing the learning experiments differed; all participants were randomly assigned into the four following groups: a) participants who first underwent OL and then WOML, moving from smartphones to laundry detergent (23 participants); b) participants who first underwent WOML and then OL, moving from smartphones to laundry detergent (23 participants); c) participants who first underwent OL and then WOML, moving from laundry detergent to smartphones (23 participants); and d) participants who first underwent WOML and then OL, moving from laundry detergent to smartphones (24 participants). This kind of counterbalancing can help reduce the bias that could result from the order in which a condition or product is provided.

Materials with the same product involvement were identical in the control groups, and the same experiment rating scale was completed after each experiment. The experiment lasted approximately 42 minutes, and participants could seek help from the experimenters at any time. The specific process was as follows: a) participants were randomly divided into four groups and had access to one computer in the laboratory; b) experimental rating scales were sent to the participants, and they received information on background knowledge and guidelines; and c) the participants filled in the questionnaire through browsing the controlled material, then filled in the questionnaire again after browsing the corresponding experimental material in Figure 2.

4.1.3. Results of study 1

Manipulation check. We first conducted a manipulation check of the variable product involvement. All 93 participants were asked questions about the degree of product involvement to provide evidence for which other variables might be concurrently affected besides the degree of product involvement in the full experiment. The participants were asked to give a rating from 1 (disagree totally) to 7 (agree totally), using the product involvement scale developed by Zaichkowsky (1994). We conducted a paired *t*-test, and the results revealed that the degree of involvement for smartphones ($M = 5.883, se = 0.078$) was higher when compared with the degree of involvement for laundry detergent ($M = 3.713, se = 0.115$), and there was a significant difference in degree of involvement ($t(92) = 15.656, p = 0.000$). Therefore, in the full experiment, all 93 participants thought that a smartphone was a high-involvement

Table 1
Tests of Within-participants Effects (Huynh-Feldt).

Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Measure: SE						
PI	7.711 (115.556)	1.000 (92.000)	7.711 (1.256)	6.139	0.015	0.063
SL	139.061 (200.440)	1.844 (169.626)	75.422 (1.182)	63.828	0.000	0.410
PI*SL	3.255 (113.025)	1.697 (156.100)	1.918 (0.724)	2.649	0.083	0.028
Measure: (EE)						
PI	10.790 (65.681)	1.000 (92.000)	10.790 (0.714)	15.114	0.000	0.141
SL	120.234 (207.576)	1.873 (92.000)	64.179 (2.256)	53.289	0.000	0.367
PI*SL	5.035 (68.896)	1.733 (159.466)	2.905 (0.432)	6.724	0.003	0.068
Measure: PE						
PI	19.964 (71.481)	1 (92.000)	19.964 (0.777)	25.694	0.000	0.218
SL	151.306 (212.686)	1.883 (173.229)	80.357 (1.228)	65.449	0.000	0.416
PI*SL	10.326 (102.070)	1.919 (176.505)	5.382 (0.578)	9.307	0.000	0.092

Table 2
Contrast Results of Simple Main Effects Analysis.

Contrast[a]	Transformed Variable										
	Controlvs. OL	Control vs. WOML	OL vs. WOML	High: Control vs. OL	High: Control vs. WOML	High: OL vs. WOML	Low: Control vs. OL	Low: Control vs. WOML	Low: OL vs. WOML	OL: High vs. Low	WOML: High vs. Low
Measure: SE											
Contrast Estimate	-0.920***	-1.158***	-0.238**	-0.746***	-1.010***	-0.264**	-1.093***	-1.305***	-0.212	-0.368**	-0.316*
Std. Error	0.103	0.124	0.096	0.098	0.138	0.130	0.143	0.154	0.142	0.143	0.169
Sig.	0.000	0.000	0.015	0.000	0.000	0.045	0.000	0.000	0.140	0.012	0.064
99.1667% Confidence	-1.197	-1.493	-0.496	-1.012	-1.382	-0.615	-1.479	-1.720	-0.596	-0.755	-0.771
Interval for Difference	-0.643	-0.823	0.020	-0.481	-0.639	0.086	-0.707	-0.891	0.172	0.018	0.139
F	80.046	86.903	6.194	57.427	53.829	4.128	58.409	72.128	2.216	6.596	3.507
Partial Eta Squared	0.465	0.486	0.063	0.384	0.369	0.043	0.388	0.439	0.024	0.067	0.037
Measure: EE											
Contrast Estimate	-0.794***	-1.102***	-0.308**	-0.562***	-1.002***	-0.44***	-1.026***	-1.202***	-0.176	-0.521***	-0.256**
Std. Error	0.099	0.125	0.104	0.079	0.125	0.105	0.140	0.150	0.148	0.111	0.124
Sig.	0.000	0.000	0.012	0.000	0.000	0.000	0.000	0.000	0.238	0.000	0.042
99.1667% Confidence	-1.062	-1.440	-0.614	-0.774	-1.339	-0.725	-1.404	-1.606	-0.575	-0.821	-0.591
Interval for Difference	-0.526	-0.764	-0.002	-0.350	-0.665	-0.156	-0.648	-0.797	0.223	-0.221	0.078
F	63.777	77.366	8.773	51.198	64.256	17.453	53.508	64.286	1.410	21.955	4.264
Partial Eta Squared	0.409	0.457	0.087	0.358	0.411	0.159	0.368	0.411	0.015	0.193	0.044
Measure: PE											
Contrast Estimate	-1.008***	-1.181***	-0.173*	-0.678***	-0.975***	-0.296***	-1.338***	-1.387***	-0.049	-0.681***	-0.433***
Std. Error	0.107	0.126	0.099	0.096	0.129	0.107	0.155	0.161	0.153	0.140	0.130
Sig.	0.000	0.000	0.086	0.000	0.000	0.007	0.000	0.000	0.751	0.000	0.001
99.167% Confidence	-1.298	-1.521	-0.441	-0.936	-1.323	-0.584	-1.756	-1.820	-0.460	-1.057	-0.783
Interval for Difference	-0.719	-0.841	0.096	-0.420	-0.626	-0.009	-0.920	-0.953	0.363	-0.304	-0.083
F	88.162	87.795	3.013	50.301	56.899	7.736	74.543	74.445	0.101	23.756	11.105
Partial Eta Squared	0.489	0.488	0.032	0.353	0.382	0.078	0.448	0.447	0.001	0.205	0.108

[a] Estimable Function for Intercept
*** $p < 0.01$,
** $p < 0.05$,
* $p < 0.1$; standard errors are reported in parentheses.

product and laundry detergent was a low-involvement product.

We conducted a 2*3 repeated-measures analysis of variance (ANOVA) using SPSS Statistics to determine whether any change in the efficiency of consumers' online shopping decision making was the result of different types of social learning, different product involvement degrees, or their interaction effects. We first carried out five assumption tests required by this methodology to ensure the validity of the results using the repeated-measures ANOVA and found that the data in this study satisfied the assumptions. There were no significant differences in the data as assessed by inspection of a boxplot. The dependent variables were normally distributed as assessed by a Shapiro–Wilk test ($p > 0.05$). The data met the sphericity criteria as evaluated using Mauchly's test. The results of the repeated-measures ANOVA are following. We note that depending on the results of Mauchly's test of sphericity, an Epsilon Huynh–Feldt correction may be used to adjust the degrees of freedom of the averaged tests of significance. Thus, the corrected tests are displayed in the table showing the results of the tests for within-participants effects (see Table 1).

The results revealed that the degree of product involvement, social learning, and their interaction had significant impacts on the efficiency of consumers' online shopping decision making at all three stages (search: main effect of product involvement: $F = 6.139$, $p = 0.015$,social learning:$F = 63.828$, $p = 0.000$, interaction: $F = 2.649$, $p = 0.083$; Evaluation: main effect of product involvement: $F = 15.114$, $p = 0.000$, social learning: $F = 53.289$, $p = 0.000$, interaction: $F = 6.724$, $p = 0.003$; Purchase: main effect of product involvement: $F = 25.694$, $p = 0.000$,social learning: $F = 65.449$, $p = 0.000$,interaction: $F = 9.307$, $p = 0.000$). However, the repeated-measures ANOVA is an omnibus test and cannot tell us which specific groups within each factor are significantly different from one other. It only tells us that at least two of the groups were different. Thus, we further conducted a simple main-effects analysis to determine in more detail how the within-participants factors affected the efficiency of consumers' online shopping decision making. The results are summarized and shown in Table 2.

4.1.3.1. Effect of social learning on online shopping. We analyzed both the learning group and control group of the high- and low-involvement products to examine the effect of social learning on online shopping. The findings are shown in Figure 3.

At the search stage, the following findings were established: a) the OL group (*mean* $= 1.736$, *se* $= 0.100$) showed a significantly higher effect than the control group (*mean* $= 0.816$, *se* $= 0.044$; $F = 80.046$, $p = 0.000$); b) the result for the WOML group (*mean* $= 1.974$, *se* $= 0.117$) was significantly higher than that of the control group ($F = 86.903$, $p = 0.000$); and c) the result for the WOML group was significantly higher than that of the OL group ($F = 6.194$, $p = 0.015$). At the evaluation stage, the following was found: a) the result for the OL group (*mean* $= 1.512$, *se* $= 0.101$) was significantly higher than that of the control group (*mean* $= 0.791$, *se* $= 0.052$; $F = 63.777$, $p = 0.000$); b) the result for the WOML group (*mean* $= 1.820$, *se* $= 0.133$) was significantly higher than that of the control group ($F = 77.366$, $p = 0.000$); and c) the result for the WOML group was significantly higher than that of the OL group ($F = 8.773$, $p = 0.012$). At the purchase stage, the following was found: a) the result for the OL group (*mean* $= 1.898$, *se* $= 0.116$) was significantly higher than that of the control group (*mean* $= 0.890$, *se* $= 0.066$; $F = 88.162$, $p = 0.000$); b) the result for the WOML group (*mean* $= 2.070$, *se* $= 0.127$) was significantly higher than that of the control group ($F = 87.795$, $p = 0.000$); and c) the result for the WOML group was significantly higher than that of the OL group ($F = 3.013$, $p = 0.086$). Overall, at the three stages, the result for the WOML group was significantly higher than that of the OL group. In addition, OL had a greater impact at the purchase stage than at the search stage ($t = 2.125$, $p = 0.035$) and had the lowest impact at the evaluation stage ($t_{b\&e} = 6.123$, $p = 0.000$; $t_{s\&e} = 4.056$, $p = 0.000$). The impact of WOML at the purchase stage was not different from that at the search stage ($t = 1.332$, $p = 0.185$), while the impact at the evaluation stage was smaller ($t_{b\&e} = 3.687$, $p = 0.000$; $t_{s\&e} = 2.324$, $p = 0.021$). Thus, the above results support hy-

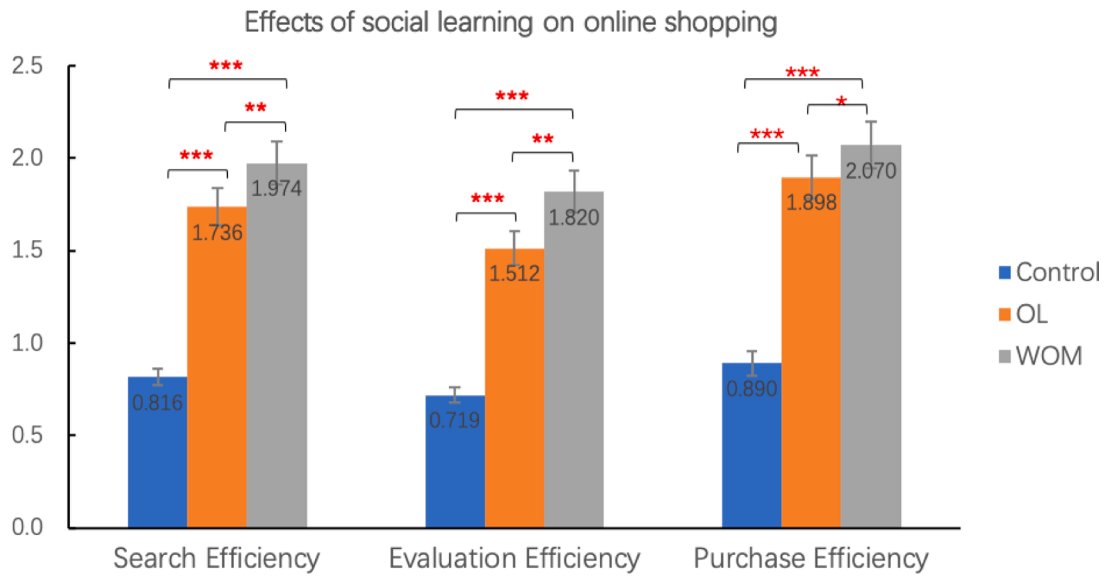

Fig. 3. Effect of social learning on online shopping.

pothesis H1. Social learning has a significant positive influence on the decision efficiency of online shopping for different involvement products.

4.1.3.2. Different effects of social learning with different levels of product involvement. To examine the moderating effect of product involvement on online shopping, we analyzed the results from the repeated-measures ANOVA (Table 1) and the simple main effects analysis (Table 2). The interaction of social learning and product involvement had a significant impact on online shopping at the search stage ($F = 2.649,\ p = 0.083$), evaluation stage ($F = 6.724,\ p = 0.003$), and purchase stage ($F = 9.307,\ p = 0.000$). The specific findings are discussed below.

High-involvement product: Effect of social learning on online shopping. We analyzed both the learning group and control group of the product with a high degree of involvement to examine the effect of social learning on online shopping for high-involvement products. The findings are shown in Figure 4.

At the search stage, the following was found: a) the result for the OL group ($mean = 1.552,\ se = 0.101$) was significantly higher than that of the control group ($mean = 0.806,\ se = 0.052; F = 57.427, p = 0.000$); b) the result for the WOML group ($mean = 1.816,\ se = 0.133$) was significantly higher than that of the control group ($F = 53.829, p = 0.000$); and c) the result for the WOML group was significantly higher than that of the OL group ($F = 4.128, p = 0.045$). At the evaluation stage, the following was found: a) the result for the OL group ($mean = 1.252,\ se = 0.066$)was significantly higher than that of the control group ($mean = 0.690,\ se = 0.040; F = 51.198, p = 0.000$); b) the result for the WOML group ($mean = 1.692,\ se = 0.115$) was significantly higher than that of the control group ($F = 64.256, p = 0.000$); and c) the result for the WOML group was significantly higher than that of the OL group ($F = 17.453, p = 0.000$). At the purchase stage, the following was found: a) the result for the OL group ($mean = 1.557,\ se = 0.107$) was significantly higher than that of the control group ($mean = 0.879,\ se = 0.070; F = 50.301, p = 0.000$); b) the result for the WOML group ($mean = 1.854,\ se = 0.125$) was significantly higher than that of the control group ($F = 56.899, p = 0.000$); and c) the result for the WOML group was significantly higher than the OL group ($F = 7.736, p = 0.007$). Overall, at each of the three stages for high-involvement products, the result for the WOML group was significantly higher than that of the OL group. Thus, the results for the high-involvement product verify hypothesis H1a and partially support hypothesis H1b. WOML has a greater influence on online shopping decisions than OL when consumers purchase high-involvement products. In addition, the effect of OL for the high-involvement group at the purchase stage was not different from that at the search stage ($t_{high} = 0.052, p = 0.959$), and both were greater than that at the evaluation stage ($t_{s\&e} = 3.651, p = 0.000; t_{b\&e} = 3.743, p = 0.000$). The effect of WOML for the high-involvement group at the purchase stage was greater than that at the evaluation stage ($t_{b\&e} = 1.803, p = 0.075$), whereas there were no differences between the other two stages ($t_{s\&e} = 1.409, p = 0.162; t_{b\&e} = 0332., p = 0.740$).

Low-involvement product: Effect of social learning on online shopping. We analyzed both the learning group and the control group for the product with a low degree of involvement to examine the effect of social learning on online shopping of low-involvement products. The findings are shown in Figure 5.

At the search stage, the following was found: a) the result for the OL group ($mean = 1.920,\ se = 0.141$) was significantly higher than that of the control group ($mean = 0.827,\ se = 0.059; F = 58.409, p = 0.000$); b) the result for the WOML group ($mean = 2.132,\ se = 0.155$) was significantly higher than that of the control group ($F = 72.128, p = 0.000$); and c) there was no significant difference between the WOML and OL groups ($F = 2.216, p = 0.140$). At the evaluation stage, the following was found: a) the result for the OL group ($mean = 1.773,\ se = 0.135$) was significantly higher than that of the control group ($mean = 0.747,\ se = 0.058; F = 53.508, p =$

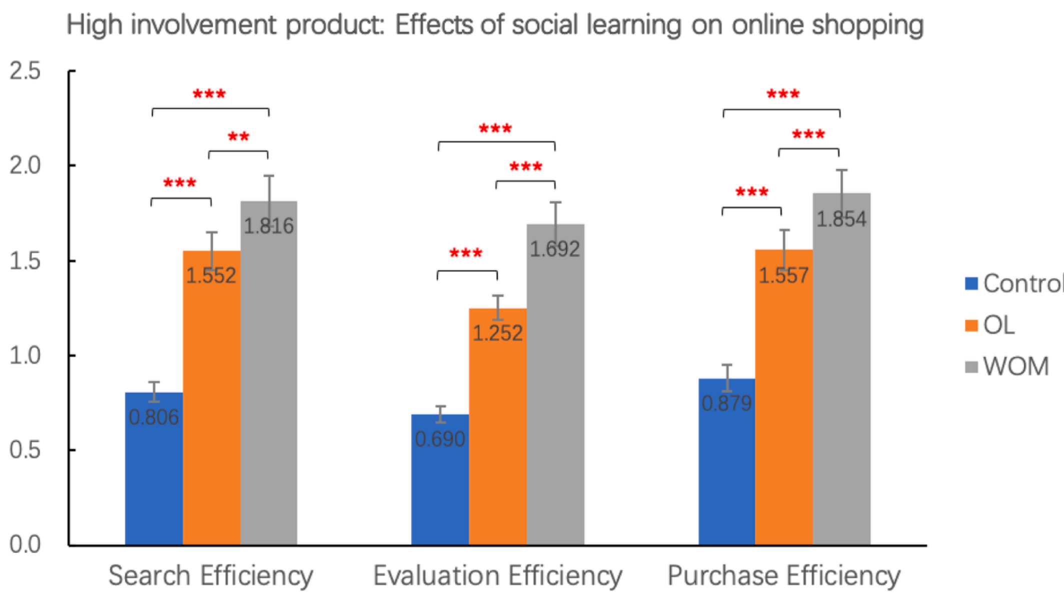

Fig. 4. Effect of social learning on online shopping for the high-involvement product.

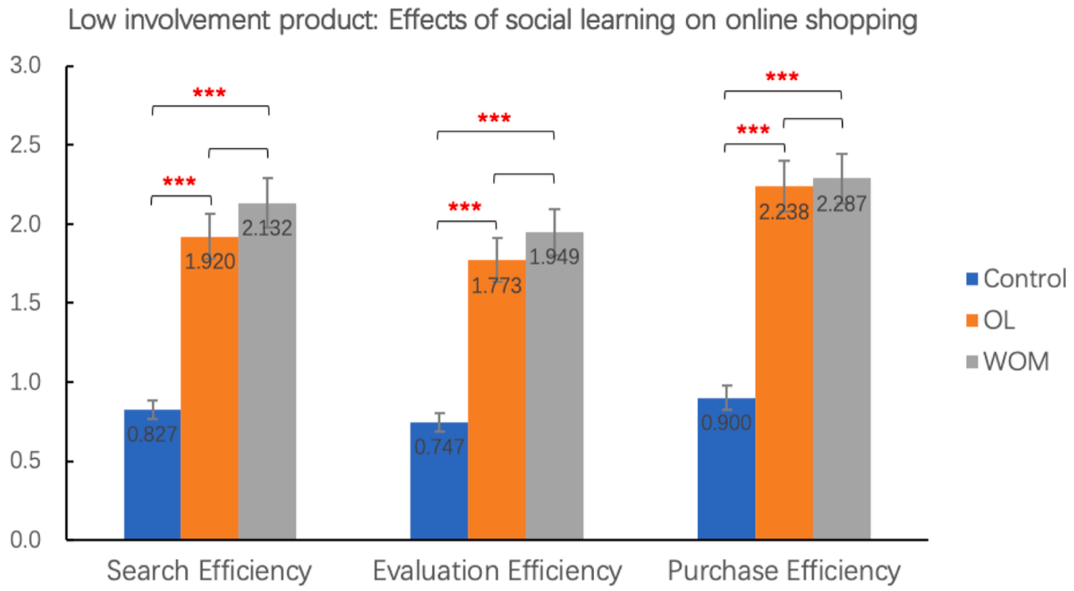

Fig. 5. Effect of social learning on online shopping for the low-involvement product.

0.000); b) the result for the WOML group ($mean = 1.949$, $se = 0.144$) was significantly higher than that of the control group ($F = 64.286, p = 0.000$); and c) there was no significant difference between the WOML and OL groups ($F = 1.410, p = 0.238$). At the purchase stage, the following was found: a) the result for the OL group ($mean = 2.238$, $se = 0.158$) was significantly higher than that of the control group ($mean = 0.900$, $se = 0.077$; $F = 74.543, p = 0.000$); b) the result for the WOML group ($mean = 2.287$, $se = 0.159$) was significantly higher than that of the control group ($F = 74.445, p = 0.000$); and c) there was no significant difference between the WOML and OL groups ($F = 0.101, p = 0.751$). Thus, the results for the low-involvement product verify hypothesis H1a and partially reject our hypothesis H1b. When shopping for low-involvement products, social learning has a significant positive influence on the decision efficiency of online shopping. However, there were no significant differences between the WOML and OL groups in all three stages of online shopping. In addition, the effect of OL for the low-involvement group at the purchase stage was larger than that at the search stage ($t = 2.906, p = 0.005$), and the impact was smallest at the evaluation stage ($t_{s\&e} = 2.013, p = 0.047$; $t_{b\&e} = 4.868, p = 0.000$). The effect of WOML for the low-involvement group at the purchase stage was larger than it was at the search stage ($t = 1{,}723, p = 0.088$), and the impact was smallest at the evaluation stage ($t_{s\&e} = 1.850, p = 0.068$; $t_{b\&e} = 3.337, p = 0.001$).

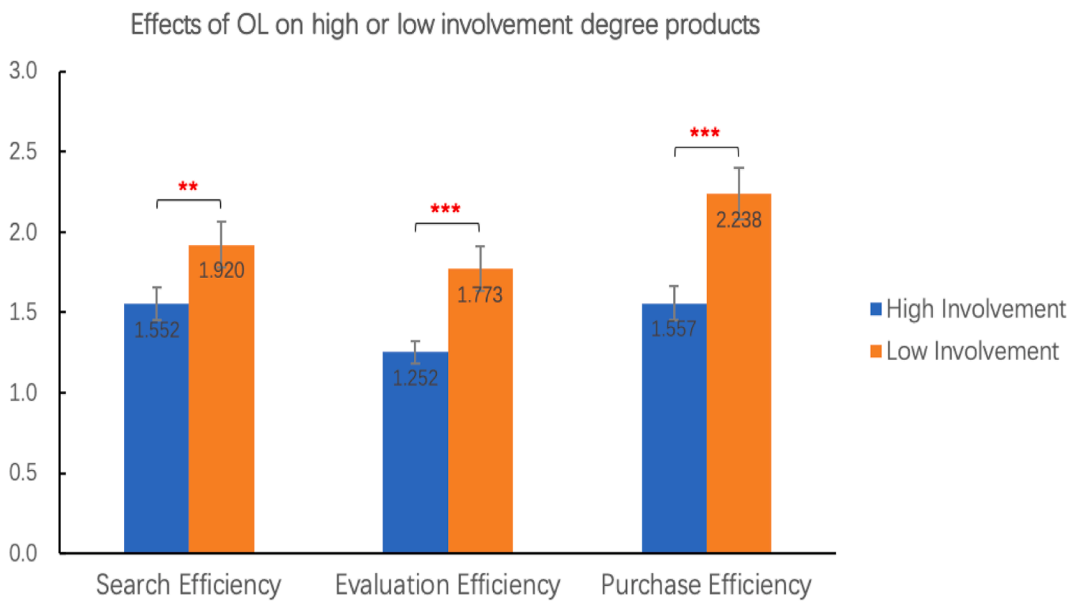

Fig. 6. Effect of OL on online shopping for high- and low-involvement products.

4.1.3.3. Additional findings. Our results brought forward other interesting findings, which are described below.

Differences in the OL effects on online shopping: High* versus *low levels of involvement. To examine the different effects of OL on online shopping for products with different levels of involvement, we calculated the different values between the OL group and the control group for high and low involvement separately and then compared them. The findings are shown in Figure 6.

The following findings emerged: a) at the search stage, the result for the low-involvement product group ($mean = 1.920,\ se = 0.141$) was significantly higher than that of the high-involvement product group ($mean = 1.552,\ se = 0.101;\ F = 6.596, p = 0.012$); b) at the evaluation stage, the result for the low-involvement product group ($mean = 1.773,\ se = 0.135$) was significantly higher than that of the high-involvement product group ($mean = 1.252,\ se = 0.066;\ F = 21.955, p = 0.000$); and c) at the purchase stage, the result for the low-involvement product group ($mean = 2.238,\ se = 0.158$) was significantly higher than that of the high-involvement product group ($mean = 1,557,\ se = 0.107;\ F = 23.756, p = 0.000$). Overall, at each of the three stages, the result for the low-involvement group was significantly higher than that of the high-involvement group.

Differences in the effects of WOML on online shopping: High* versus *low levels of involvement. We compared the high-involvement WOML group with the low-involvement WOML group to examine the differences in the effects of WOML on online shopping for products with different levels of involvement. The findings are shown in Figure 7.

The following was found: a) at the search stage, the result for the low-involvement product group ($mean = 2.132,\ se = 0.155$) was significantly higher than that of the high-involvement product group ($mean = 1.816,\ se = 0.133;\ F = 3.507, p = 0.064$); b) at the evaluation stage, the result for the low-involvement product group ($mean = 1.949,\ se = 0.144$) was significantly higher than that of the high-involvement product group ($mean = 1.692,\ se = 0.115;\ F = 4.264, p = 0.042$); and c) at the purchase stage, the result for the low-involvement product group ($mean = 2.287,\ se = 0.159$) was significantly higher than that of the high-involvement product group ($mean = 1,854,\ se = 0.125;\ F = 11.105, p = 0.001$). Overall, at each of the three stages, the result for the low-involvement group result was significantly higher than that of the high-involvement group.

4.2. Study 2: survey and structural model analysis

Based on motivation reinforcement theory, the goal of study 2 was to explore the following: a) the mediating factors for social learning and the efficiency of online shopping and b) the moderating role of product involvement on the above relationships.

4.2.1. Data collection

The data were collected from April 15, 2019 to May 25, 2019, and 475 valid questionnaires out of 505 were returned, with an effective response rate of 90.1%. Of the respondents, 52.6% were male, and 47.4% were female. Most respondents (69.5%) were younger than 20 years old, and 83.8% had a college education. The income of 94.7% of the respondents was less than 3000 yuan. The respondents all had some online shopping experience. According to the China Internet Network Information Center in 2018, people aged 18 to 30 years comprise the highest proportion of the population of web users, and this population segment consists mainly of college students with bachelor's or graduate degrees. We collected data by randomly interviewing students on campus. Table 3 summarizes the demographic statistics of the sample.

We used SPSS and WarpPLS3.0 to analyze the data. We used WarpPLS3.0 for three reasons: a) it can assess structural models and measurement models, as well as measure the linear and nonlinear relationships among variables of an integrated models; b) it can measure both pre-variables and intermediate variables; and c) predictive accuracy is particularly important since the sample size is not large.

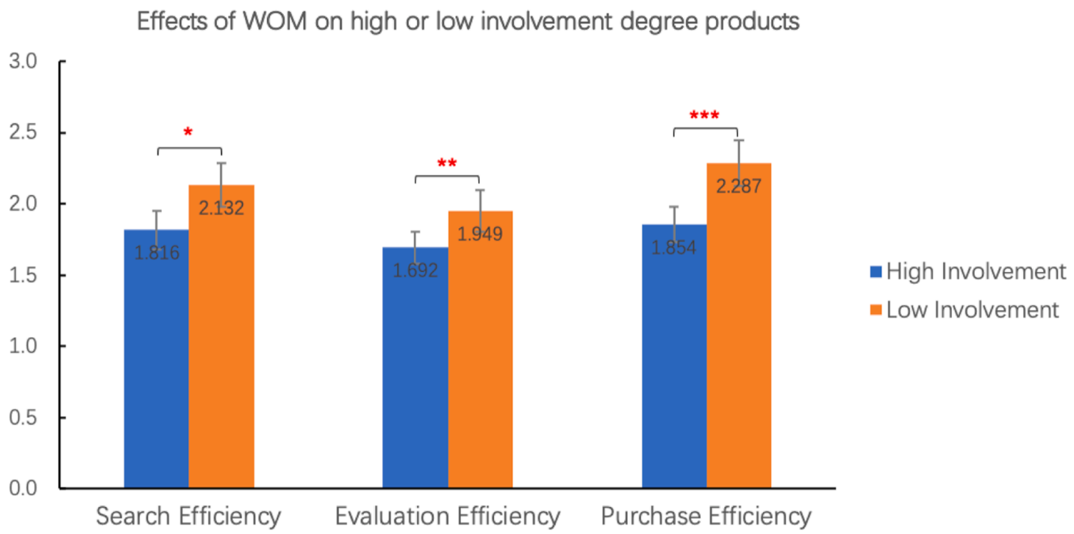

Fig. 7. Effect of WOML on online shopping for high- and low-involvement products.

Table 3
Demographic Statistics.

Measure	Item	Number	Percentage (%)
Gender	Male	250	52.6%
	Female	225	47.4%
Age	< 18	58	12.2%
	18–22	213	44.8%
	22–30	176	37.2%
	> 30	28	5.8%
Education	College/University	296	62.2%
	Master	126	26.5%
	Doctoral	53	11.3%

4.2.2. *Survey design and procedure*

The questionnaire had two parts. The first part focused on demographic data, while the second focused on the theme of the research (see Figure 1), including product search, product selection and evaluation, product purchase decisions, learning effects, and product involvement, which are the same with the scale in Study 1. In addition, there is a scale for extrinsic and intrinsic reinforcement, which was adapted from Mcauley, et al. (1989).

A pilot study ensured the accuracy of measurement and the validity of the questions, and the final questionnaire contained 40 questions. We employed a 7-point Likert scale (1 = totally disagree, 7 = totally agree). The pilot study lasted from March 5, 2019 to March 20, 2019, resulting in 152 valid questionnaires out of 180. We further modified the questionnaire according to the results of the pilot study.

All factor loadings were significant at the 0.001 level, indicating acceptable convergent validity at the item level. All average variances extracted (AVEs) were greater than 0.5, indicating acceptable convergent validity at the construct level. All Cronbach's alpha values were greater than 0.8, and composite reliabilities ranged from 0.7 to 0.8, suggesting acceptable reliability (Fornell & Larcker, 1981). The square root of the AVE of the focal construct was greater than the correlation between the focal construct and other constructs, indicating acceptable discriminant validity. As shown in Table 4, the correlations of the inter-constructs were relatively low (< 0.6), indicating no undue common method bias present in the data.

The variance inflation factor (VIF) was also calculated to check the collinearity by following the procedure suggested in (Hair et al., 1998). The results showed that both VIFs and Full Collin VIFs were less than 5 (Tables 5 and 6), which demonstrated that no collinearity existed (Asher, 1983; Hair et al., 1998). Therefore, the measurement model is acceptable.

The overall goodness-of-fit enables us to test the structural model, including the average path coefficient (APC), average R-squared (ARS), and average VIF (AVIF). The APC and ARS of the model were both significant ($p < 0.001$) and AVIF was less than 5 (see Table 7), indicating the overall fit of the structural model.

4.2.3. *Results of study 2*

In this study, the effect size coefficient is calculated according to Cohen's method, which is useful for analyzing direct effects, indirect effects and total effect constants.

Following the structural equation modeling approach (Richard P Bagozzi, Yi, & Phillips, 1991), Figure 8 presents the results of the structural model with the standardized path coefficients between constructs.

The R^2 value of the dependent variable represents the predictive power of the theoretical model. This model explained 25% of the variance of extrinsic reinforcement (ER), 22% of the variance of intrinsic reinforcement (IR), 44% of the variance of search efficiency (SE), 40% of the variance of evaluation efficiency (EE), and 89% of the variance of purchase efficiency (PE), so we may consider the results valid.

According to the results, "OL" had a significant positive effect on "ER" ($\beta = 0.390$, $p < 0.001$); "WOML" had a significant positive effect on "IR" ($\beta = 0.383$, $p < 0.001$); "OL" had no significant positive effect on "IR" ($\beta = 0.024$, $p = 0.298$); "WOML" had no significant negative effect on "ER" ($\beta = -0.043$, $p = 0.173$); "ER" ($\beta = 0.620$, $p < 0.001$) and "IR" ($\beta = 0.292$, $p < 0.001$) had significant positive effects on "SE," "ER" ($\beta = 0.132$, $p < 0.001$); and "IR" ($\beta = 0.228$, $p < 0.001$) had significantly positive effects on "EE". Moreover, "ER" had no significant positive effects on "PE" ($\beta = 0.036$, $p = 0.218$), and "IR" had significant positive effects on "PE" ($\beta = 0.715$, $p <$

Table 4
The correlations of inter-constructs.

Construct	OL	WOML	ER	IR	SE	EE	PE	PI
OL	**0.670**							
WOML	-0.010	**0.621**						
ER	0.393	-0.043	**0.780**					
IR	0.010	0.412	-0.120	**0.786**				
SE	0.300	0.174	0.581	0.234	**0.646**			
EE	0.086	0.212	0.112	0.317	0.523	**0.812**		
PE	0.049	0.314	-0.075	0.827	0.337	0.588	**0.729**	
PI	0.066	0.296	-0.394	0.335	-0.091	0.071	0.306	**0.722**

Table 5
VIF values for all variables.

Index (VIF)	OL	WOML	PI * OL	PI * WOML
ER	1.004	1.003	1.001	
IR	1.003	2.398		2.398

Table 6
Full Collin VIF values.

Construct	OL	WOML	ER	IR	SE	EE	PE	PI	PI*OL	PI*WOML
VIF	1.218	1.433	2.293	4.313	2.389	2.312	5.292	1.543	1.061	1.338

Table 7
The overall goodness-of-fit.

Index	**Model**
APC	APC = 0.286, p < 0.001
ARS	ARS = 0.405, p < 0.001
AVIF	AVIF = 1.289, Good if < 5

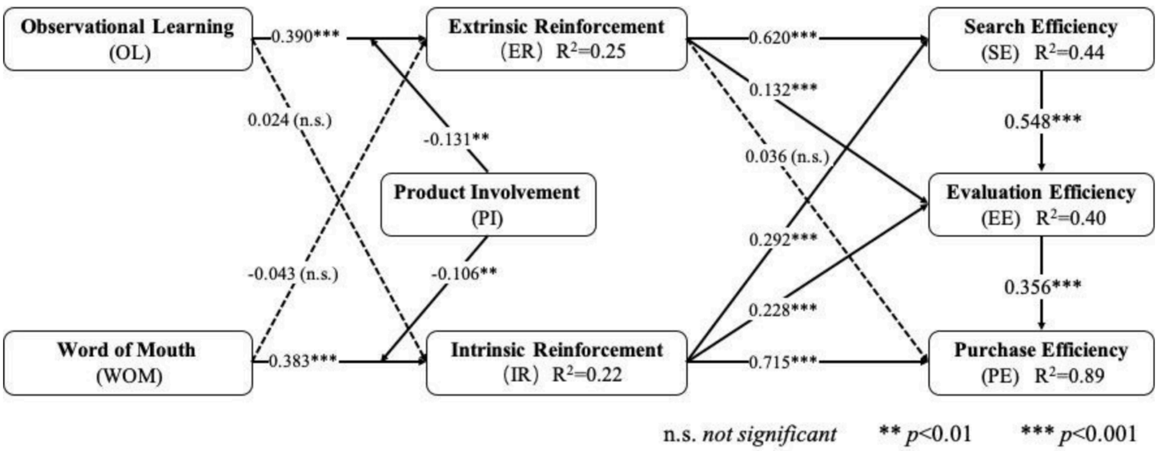

Fig. 8. Structural model with standardized coefficients and fit indexes.

0.001). Thus, the results support hypothesis H2a. OL has a significant positive extrinsic reinforcement on consumers' motivations, influencing the decision efficiency of online shopping except at the purchase stage. WOML has a significant positive intrinsic reinforcement on consumers' motivations, influencing the decision efficiency of the three online shopping stages.

Product involvement had a significant negative moderating role in the relationship between OL and motivation reinforcement ($\beta = -0.131$, $p < 0.01$). Moreover, product involvement had a significant negative moderating role in the relationship between WOML and motivation reinforcement ($\beta = -0.106$, $p < 0.01$). Thus, the results support hypothesis H2b. Product involvement has a significant negative moderating role in the relationship between social learning and motivation reinforcement.

Next, we investigated the associated mechanisms of mediating variables (i.e., IR and ER) in the occurrence of OL, WOM and PE. In testing the significance of mediating effects, we used the rigorous and powerful bootstrap method (MacKinnon et al., 2002), with the number of bootstrap samples set to 5000. The results are shown in Table 8 and Table 9. As shown in Table 8, OL has a significant total influence on PE ($\beta = 0.089$, $p = 0.007$), and WOM also has a significant total influence on PE ($\beta = 0.302$, $p < 0.001$). The total effect is the sum of the direct and indirect effects between the latent variables.

As shown in Table 9, after the introduction of the mediating variables (i.e., IR and ER), there were differences in the effects of OL or WOM on PE. Specifically, OL has a significant indirect effect on 4 segments that are connected to PE i.e., OL-ER-SE-EE-PE; while WOM

Table 8
The total effects.

	coefficient	P value	Boot SE	Value Effect
OL-PE	0.080	**0.007**	0.032	0.004
WOM-PE	0.302	**< 0.001**	0.031	0.095

has a significant indirect effect on 2 segments that are connected to PE, i.e., WOM-IR-PE. The WOM-IR-PE route has a particularly powerful indirect effect; its effect value is 0.080. This route is the most significant pathway for the indirect effect of WOM on PE. Thus, the results of the bootstrap test further support hypothesis H2a. OL has a significant positive effect on consumers' extrinsic motivation reinforcement, and influences the decision efficiency of consumers' decision processes from the first stage of decision making (i.e., search) to the final stage (i.e., purchase). WOML has a significant positive effect on consumers' intrinsic motivation reinforcement, and thereby influences purchase efficiency.

5. Discussion

Numerous prior studies have measured the effect of OL or WOML on consumers' consumption decisions (Chevalier & Mayzlin, 2006; Gilal et al., 2019; Godes & Mayzlin, 2004; Hanson & Putler, 1996; Xinxin Li et al., 2011; Liu, 2006; Nakayama & Wan, 2021; Salganik et al., 2006; Soltysinski & Dholakia, 2001; J. Zhang, 2010; Zhuang et al., 2018), but few studies have investigated the differences between the effects of OL and WOML (Y. Chen et al., 2011; Cheung et al., 2014; Herhausen et al., 2019; Xitong Li & Wu, 2013). In addition, prior studies have tended to treat consumers' consumption decisions as the ultimate outcomes of their model to understand how social learning affects consumers' final purchase decisions (Y. Chen et al., 2011; Cheung et al., 2014; Xitong Li & Wu, 2013). Most consumer purchase decisions are not disconnected actions but complex processes, which can be considered problem-solving processes (i.e., search, evaluation, and purchase) (Engel et al., 1993). Consumers often add products to their shopping carts but do not make a final purchase decision. Even fewer studies have considered the path from social learning to transaction because frequent interactions in virtual environments may not endorse the probability of an eventual sale (Y. Wang & Yu, 2017). In the current competitive market environment, sellers urgently want to understand how to affect consumers' buying process from the first step to the final decision, and then develop more targeted marketing strategies at different stages.

In this research, we conducted two studies: a behavior experiment (study 1) and a survey (study 2). Study 1 showed the significant and differential influences of social learning on the efficiency of the consumer decision process. Study 2 explored the impact of motivation reinforcement in the context of social learning and the efficiency of online shopping, and it further highlighted the moderating effect of product involvement. The results of the hypothesis testing are shown in Table 10.

5.1. Key findings

According to the results from both studies 1 and 2, we can articulate the following findings. First, social learning (both OL and WOML) has significant positive effects on product search, evaluation, and purchase decisions in the online shopping process. In addition, the effect of social learning is stronger when shopping for low-involvement products than when shopping for high-involvement products. This may be because when consumers are shopping for low-involvement products that are less related to their needs and interests, consumers hope to save their time and energy and may be inclined to follow other consumers. Hence, their decision-making processes are more influenced by social learning than when shopping for high-involvement products. Since high-involvement products are highly related to consumers' needs and interests, consumers have clearer preferences and more independent considerations than when shopping for low-involvement products. Therefore, consumers shopping for high-involvement products will not be as substantially affected by social learning as consumers shopping for low-involvement products. In addition, they have sufficient patience and energy to collect more informative and complex information; for example, they are more willing to rely on WOML to obtain information that is more comprehensive than simple OL (e.g., sales rankings).

Second, when shopping for high-involvement products, there were significant differences between the WOML and OL groups in all three stages of online shopping. WOML has a stronger significant positive influence on the decision efficiency of online shopping than OL. This may be because consumers are more interested in complex and comprehensive WOML than in simple OL (e.g., sales rankings) when shopping for high-involvement products. However, when shopping for low-involvement products, there were no significant differences between the WOML and OL groups in the three stages of online shopping. This may be because consumers are not inclined to rely on social learning while shopping for low-involvement products. Both OL and WOML are equally important to consumers.

Third, social learning had a significant positive reinforcement effect on consumers' motivation, influencing the decision efficiency of online shopping. Specifically, OL reinforced consumers' extrinsic motivation, while WOML reinforced consumers' intrinsic motivation; hence, they positively influence the decision efficiency of online shopping. Product involvement has a significant negative moderating role in the relationship between social learning and motivation reinforcement.

Table 9
The indirect effects.

		coefficient	P value	Boot SE	Value Effect
OL-PE	OL-PE (OL-ER-PE)	0.014	0.333	0.032	0.001
	OL-PE (OL-ER-EE-PE)	0.018	0.243	0.026	0.001
	OL-PE (OL-ER-SE-EE-PE)	0.048	**0.019**	0.023	0.002
WOM-PE	WOM-PE (WOM-IR-PE)	0.253	**< 0.001**	0.031	0.080
	WOM-PE (WOM-IR-EE-PE)	0.029	0.139	0.026	0.009
	WOM-PE (WOM-IR-SE-EE-PE)	0.020	0.189	0.023	0.006

Table 10
The results of hypothesis testing.

Research Hypotheses	Study 1	Study 2
H1: Social learning has a significant positive and differential influence on the decision efficiency of the online shopping process.	**Y**	**Y**
H1a: Both OL and WOML have significant positive influences on the efficiency of the online shopping process.	*Y****	*Y****
H1b: OL and WOML have significant differential influences on the efficiency of online shopping process. Specifically, *WOML has a greater influence on online shopping process than OL when consumers purchase high-involvement products, while OL has a greater influence on online shopping process than WOML when consumers purchase low-involvement products.*	*Y (Partially)*	*Y****
H2: Social learning has a significant and positive reinforcement effect on motivation, influencing the decision efficiency of the online shopping process.		**Y**
H2a: OL will reinforce consumers' extrinsic motivations, while WOML will reinforce consumers' intrinsic motivations; hence, OL and WOML positively influence the decision efficiency of the online shopping process.		*Y****
H2b: Product involvement plays a significant and negative moderating role in the relationship between social learning and motivation reinforcement.		*Y****

5.2. Theoretical implications

With the vigorous development of e-commerce in recent years, many popular e-commerce sites have applied observational and WOM information. Both scientific research and business practice have proved the necessity and importance of social learning in consumers' decision making. In line with a growing branch of inquiry in the literature (Chevalier & Mayzlin, 2006; Gilal et al., 2019; Godes & Mayzlin, 2004; Hanson & Putler, 1996; Herhausen et al., 2019; Xinxin Li et al., 2011; Liu, 2006; Salganik et al., 2006; Soltysinski & Dholakia, 2001; J. Zhang, 2010; Zhuang et al., 2018), we studied the influence of two main methods of social learning related to online shopping decisions, OL and WOML. Specifically, we examined whether and how OL and WOML influenced consumers' decision efficiency at three online shopping stages (i.e., search, evaluation, and purchase) for products with different degrees of involvement against the backdrop of e-commerce. This study has several theoretical implications.

Based on our findings, the framework and results of this research offer useful insights regarding the academic contribution. First, this study contributes to the stream of social learning literature by considering three stages of online shopping (i.e., search, evaluation, and purchase) to examine the different influences of OL and WOML on online shopping decision efficiency. The role of OL or WOML in online shopping has been emphasized in current related research. Prior research has shown that OL or WOML affects consumer purchase decisions (Chevalier & Mayzlin, 2006; Gilal et al., 2019; Godes & Mayzlin, 2004; Hanson & Putler, 1996; Xinxin Li et al., 2011; Salganik et al., 2006; Soltysinski & Dholakia, 2001; J. Zhang, 2010; Zhuang et al., 2018). A few studies compared the differences between the effects of OL and WOML on final product sales (Y. Chen et al., 2011; Cheung et al., 2014; Herhausen et al., 2019; Y. Wang & Yu, 2017); however, the effect of social learning in e-commerce may not contribute to final product sales. Our paper focused on the effects of OL and WOML at different stages in the online shopping process from the perspective of decision making.

Second, we established a structural equation model to study intrinsic and extrinsic motivation reinforcement as mediating factors to reveal the influence mechanisms of OL and WOML against the backdrop of e-commerce. Prior studies have drawn on various information theories, such as signal theory (Cheung et al., 2014) and information cascade theory (Y. Wang & Yu, 2017), to understand the impact of OL or WOML. This study drew on motivation reinforcement theory from the perspective of social psychology to better understand how information technology influences people's social and commercial behaviors. Our findings showed that OL influences the consumer's decision efficiency via extrinsic reinforcements of motivation, while WOML influences the consumer's decision efficiency via intrinsic reinforcements of motivation.

Third, this study investigated the moderating role of product involvement in the relationships between OL or WOML and consumers' decision efficiency at different shopping stages to enrich the literature on product involvement in the field of social learning research. Prior studies have demonstrated a few moderating factors, such as consumer expertise (Cheung et al., 2014); however, product involvement is another significant factor influencing consumers' buying decisions (Hong, 2015) that can be considered in exploring the effect of social learning on online shopping. For different product involvement levels, there are differences in the degree of consumer concern and participation, the amount of information that consumers need, and the effect of their social learning methods. The results of this study showed that product involvement has a significant negative moderating role on the relationships between OL or WOML and consumers' decision efficiency at different shopping stages, and further explores the moderating role of product involvement in the relationships between OL or WOML and consumer motivations.

5.3. Practical implications

Our research results can provide effective clues for online businesses, such as electronic shopping, applications, electronic music, and other online store operators and platform administrators, to assist in the development of their online marketing strategies.

First, for sellers and platform managers, social learning information should be provided to consumers effectively. For OL information, e-commerce platforms or sellers should pay attention to their background data statistics and reports from third-party agencies, and use user portraits and big data technology to build a more meticulous and intuitive information model. For WOML information, e-commerce platforms or sellers should encourage and guide consumers to contribute high-quality, objective comments, such as in evaluation reports and buyers' shows. In addition, apart from presenting digital and written comments, more referable types of WOML should be developed in addition to optimization of the design and display of new reputational content, such as videos, images, and audio. Meanwhile, the weight of OL information (e.g., sales volume and all rankings) should be the focus on the show page of search boxes and search results for low-involvement products.

Second, in order to assistant the proper marketing decisions, sellers and platform managers should identify the different product types which might stimulate consumers' extrinsic or intrinsic motivation. The majority products of online shopping are motivated by extrinsic factors of the customers such as convenience, competitive pricing, greater access to information, and lower search cost (Bakos, 1997). Our finding showed that OL have influenced the consumers' decision efficiency via extrinsic reinforcements of motivation so that online sellers and platform should provide more OL information. However, with consumers' increasing demands for entertainment, more and more products, which are related to intrinsic motivations such as perceived enjoyment, are presented. Our finding showed that WOML have influenced the consumers' decision efficiency via intrinsic reinforcements of motivation. Thus, the webpage of products about intrinsic motivations should highlight WOM information, for example, tourism services.

Third, content-consumption online shops should make full use of social learning information at the different stages and interfaces of the purchasing path. Since social learning has significant positive effects on the product search, product selection and evaluation, and product purchase decisions of both high- and low-involvement products, content-consumption online shops should adequately provide social learning information at each node of the consumer's purchase path. Then, it will be necessary to emphasize sales volume, ranking, number of positive or negative comments, and representative comments with WOML.

Fourth, social learning information shown in the consumer online shopping path should be differentiated for the different types of products and products with different levels of involvement. Currently, e-commerce covers products and services vertically, and the categories of high- and low-involvement products have been extended. Digital home appliances, real estate, and cross-border tourism commodities can now all be regarded as high-involvement products, while daily necessities, such as take-out food, videos, and music can be regarded as low-involvement products. The presentation of WOML information should be emphasized on pages providing details about high-involvement products. All these factors guarantee the convenience, effectiveness, and adequacy of social learning for consumers.

6. Limitations and future research

This study elaborated on the influence of social learning on the consumer decision process and investigated the mechanisms and the moderating role of product involvement. However, there are still some limitations to this study. First, the research sample mainly comprised college students because of our focus on campus recruitment. Future research should target other populations. Second, from the perspective of the information selection process, we focused on two social learning methods that show significant differences: numerical OL and textual WOML. In further research, researchers should explore more features of OL and WOML in online shopping, such as reviews with pictures. Finally, our exploration of decision behavior types is limited. In future studies, we plan to explore more types of decision-making behaviors, such as risk decision making or group decisions.

Authors' contribution

Fenghua Wang: Formal Analysis, Conceptualization, Methodology, Validation, Writing-Original Draft, Data Curation.
Mohan Wang: Formal analysis, Software, Investigation, Writing-Original Draft, Writing-Review & Editing, Visualization.
Yan Wan: Conceptualization, Resources, Supervision, Funding Acquisition.
Jia Jin: Writing-Review & Editing, Analysis.
Yu Pan: Conceptualization, Data Curation, Supervision, Resources, Project administration, Funding Acquisition.

Declaration of Competing Interest

None.

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