Utilitarian and/or hedonic shopping – consumer motivation to purchase in smart stores

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Abstract

Purpose – Recently, smart retail technology has emerged as an innovative technology that can improve consumer motivation and behavior in smart stores. Although prior studies have investigated factors influencing the adoption of smart retail technology, to the authors' knowledge, no previous work has investigated the determinants of purchase intentions. The ultimate goal for retailers should be shopping, not technology adoption. However, traditional brick-and-mortar stores and theories focus on investing in utilitarian factors to attract customers. This study proposes that hedonic motivation should also play an important role, as new technologies may arouse customer curiosity and increase pleasant experiences. Therefore, the purpose of this study is to explore utilitarian and hedonic motivations that promote customers' purchase; intentions in smart stores. Specifically, the authors address the research questions: (1) What are the constituents of utilitarian motivation? (2) What are the constituents of hedonic motivation? (3) What are the factors that influence customers' purchase intentions? By answering the questions, the findings help retailers understand how to motivate customers to make purchases in smart stores.

Design/methodology/approach – To investigate consumer motivation and purchase intentions, the customers who made purchases in smart stores were invited to participate in the questionnaire survey. This study collected 307 data in smart retail settings. Partial least squares (PLS) software was used to assess the reliability, validity and the paths and significance of all hypotheses.

Findings – The results show that perceived ease of use directly and indirectly influences purchase intentions through utilitarian and hedonic motivations. Utilitarian motivation is a formative second-order construct comprised of merchandise price, merchandise quality, location convenience, speed of shopping and product recommendation. Hedonic motivation is a reflective second-order construct composed of control, curiosity, joy, focused immersion and temporal dissociation. The findings provide insights into the successful implementation of smart retail technology and offer retailers to better understand consumer motivation and purchase intentions in smart stores.

Originality/value – This study is the first to examine how consumer motivation influences purchase intentions in smart stores. This study posits and verifies the extended hedonic system acceptance model (HSAM) to explain consumer motivation for shopping in smart retail settings. This study also models the original first-order utilitarian and hedonic constructs as second-order formative and reflective constructs, respectively. Utilitarian motivation regarding functional benefits is developed based on the 5Ps of marketing and situational factors, while hedonic motivation regarding pleasant experiences is proposed based on cognitive absorption.

Keywords Smart store, Hedonic system acceptance model, 5Ps, Situational factors, Utilitarian motivation, Hedonic motivation, Purchase intention

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1. Introduction

The development of smart retail technology makes shopping in retail stores more efficient and convenient than ever. Recently, retailers have implemented smart retail technologies, such as radio frequency identification systems (RFIDs), near field communication systems (NFCs), smart shopping carts, and self-checkout systems, to improve shopping experience, improve business processes, reduce operating costs and increase revenue (Roy *et al.*, 2018, 2020). Smart store conglomerates, such as Amazon Go, SmartMart, Metro Group Future store, and Boekhandels Groep Nederland (BGN), have made significant advancements to seize the retail market. According to the analysis report, the global smart retail market size reached 19.5 billion US dollars in 2020, and is expected to reach 134 billion US dollars by 2028, with a compound annual growth rate (CAGR) of 27.7% (Grand view research, 2021).

When shopping in traditional brick-and-mortar stores, customers would consider merchandise value, the physical store environment and interpersonal service (Chocarro *et al.*, 2013; Lloyd *et al.*, 2014; Verhagen and Van Dolen, 2009); that is, functional benefits are the main drivers of customer shopping. Although the purchasing process in traditional stores is somewhat similar to that of smart stores, smart stores offer a novel experience, in which no salespersons interact with customers, and yet, the store still communicates with customers to recommend products and complete checkout activities. As reported by Amazon's survey, 84% of consumers enjoy the shopping experience in smart stores more than in traditional stores (shorr, 2018).

Previous research on traditional store shopping has focused mainly on the effectiveness of functional benefits, including merchandise quality, merchandise price and store location, rather than customers' pleasant experiences (Chocarro *et al.*, 2013; Lloyd *et al.*, 2014; Verhagen *et al.*, 2009). In contrast, smart stores can stimulate customer curiosity and increase pleasant experiences through a series of innovative interactions with smart retail technology. Therefore, this study strives not only to extend the common utilitarian factors that affect traditional store shopping, but also to investigate hedonic motivation that induce customers' pleasant experiences.

With the popularity of smart stores, a few studies have examined hedonic motivation (Adapa *et al.*, 2020; Fazal-e-Hasan *et al.*, 2021; Nikhashemi *et al.*, 2021; Roy *et al.*, 2017, 2020). However, they paid attention to only a single aspect of motivation, such as novelty, enjoyment or control, which do not comprehensively reflect customers' pleasant experiences in smart stores. In addition, prior studies have mainly investigated the adoption of smart retail technologies, including augmented reality applications (Nikhashemi *et al.*, 2021), smart retailing technology (Roy *et al.*, 2017, 2018, 2020) and self-checkout systems (Collier *et al.*, 2015). However, complete transactions require that customers make purchases, which involves more than just the presence of technology. Therefore, the purpose of this study is to explore utilitarian and hedonic motivations that promote customers' purchase intentions in smart stores. More specifically, we address the following research questions:

RQ1. What are the constituents of utilitarian motivation?

RQ2. What are the constituents of hedonic motivation?

RQ3. What are the factors that influence customers' purchase intentions?

To address this knowledge gap, this study uses the hedonic system acceptance model (HSAM) to examine the roles of utilitarian and hedonic motivations on purchase intentions in smart retail settings. HSAM has been widely used to explain the use and acceptance of utilitarian and hedonic systems (van der Heijden, 2004). To extend the knowledge of consumer motivation, this study conceptualizes situational factors and cognitive absorption as sub-dimensions of utilitarian and hedonic motivations (Belk, 1975; Agarwal and Karahanna, 2000). Utilitarian motivation regarding functional benefits is comprised of merchandise quality, merchandise price, location convenience, speed of shopping and product recommendation, while hedonic motivation regarding pleasant experiences in smart stores is composed of control, curiosity, joy, focused immersion and temporal dissociation.

The contributions of this study are threefold. First, this study contributes to the literature on customers' purchase intentions in smart stores, while most studies have investigated the adoption of smart retail technology. Second, this study develops a research model extending HSAM with situational factors and cognitive absorption to model utilitarian and hedonic motivations as second-order constructs, thereby providing a comprehensive view of consumer motivation. Finally, this study provides insights into the successful implementation of smart retail technology and offers several suggestions to increase consumer motivation and purchase intentions.

The rest of this paper is structured as follows. The next section introduces the theoretical backgrounds and foundations. Section 3 presents the research model and proposes research hypotheses. Section 4 details the research methodology and data collection process. Section 5 presents the results of the data analysis, followed by a discussion of the findings in Section 6. Section 7 proposes theoretical and managerial contributions. The conclusion and future research directions are presented in the final section.

2. Literature review

2.1 Smart store

The term SMART comes from the acronym "Self-Monitoring, Analysis and Reporting Technology" (Netlingo, 2021). In other words, smart retail technology can help monitor the types of products and services customers are using, analyze customers' big data, and provide valuable reports. Recently, retailers have implemented various smart retail technologies for traditional brick-and-mortar stores, such as RFIDs, NFCs, augmented-reality interactive technology systems (ARTs), smart shopping carts and self-checkout systems.

Smart stores are brick-and-mortar stores that use smart retail technologies, such as smart shopping carts, self-checkout systems and smart recommendations, to offer a personalized, immersive and interactive shopping experience (Fan *et al.*, 2020). According to Sainsbury's definition of a smart store, a smart store utilizes new technologies to offer customers with a new shopping environment, where groceries collected are monitored, real-time recommendations are dispatched, and payments are processed via present accounts. In other words, customers can purchase, check out, and pay for their purchased items in smart stores without interaction with any salesperson. Smart stores have multiple cameras and shelves with weight sensors to monitor and track all incoming and outgoing customers and products. The technology allows for the use of smart shopping carts and self-checkout systems to effectively complete transactions. By analyzing individual customer preferences and historical transactions, smart stores provide personalized product information to facilitate the dyadic interaction between customers and smart retail technology (Gretzel *et al.*, 2015a, b). Thus, the deployment of smart stores makes customers' shopping experience more convenient and enjoyable (Roy *et al.*, 2020).

Given the characteristics and features of smart stores, this study focuses on explaining what types of consumer motivation will lead to purchase intentions. According to motivational theory (Babin *et al.*, 1994), consumer behavior in retail shopping can be driven by utilitarian and hedonic motivations. In other words, consumer behavior is determined not only by goal-oriented shopping, but also by the pleasure experienced during shopping. Utilitarian motivation refers to the degree to which customers complete the purchase task efficiently. Customers may make purchases due to low prices, price/quality ratios, the benefits of convenience, and sales promotions (Riegger *et al.*, 2021). In addition, according to a survey conducted by Amazon Go, product quality, product price, speed of shopping and location are the top four factors that influence customer shopping (shorr, 2018). On the other hand, hedonic motivation refers to the degree to which customers have pleasant experiences when shopping in smart stores. Customers may make purchases because they seek fun, play, enjoyment and experience, not just for goal-oriented shopping.

Previous studies on smart stores have focused on utilitarian motivation, such as the usefulness and ease of use of smart retail technology (Adapa *et al.*, 2020; Fazal-e-Hasan *et al.*, 2021; Nikhashemi *et al.*, 2021; Roy *et al.*, 2017, 2020). Although a few studies have employed a single construct (e.g. novelty, enjoyment, or control) to describe hedonic motivation, this construct is too simplistic to reflect customers' pleasant experiences (as Table 1). In particular, smart stores without interaction with any salesperson should pay more attention to customer experience than brick-and-mortar stores, since customers can obtain an enjoyable, pleasurable and immersive experience in the shopping environment through smart retail technology.

As advocated by Sainsbury, customers can not only complete purchase tasks at smart groceries, but also get personalized, frictionless and immersive shopping experiences enabled by smart technology. Since HSAM can explain both utilitarian and hedonic motivations, the theoretical model is adopted to investigate how customers are motivated by goal-oriented shopping and pleasure during shopping. Therefore, this study introduces a comprehensive customer experience to organize hedonic motivation and proposes a new theoretical model

Previous studies	Utilitarian motivation	Hedonic motivation	Dependent variables	Research issue
Adapa *et al.* (2020)	● Perceived complexity ● Perceived advantage ● Perceived risk	● Perceived novelty	● Intention to use	Smart retail technology
Roy *et al.* (2017)	● Relative advantage ● Personalization ● Interactivity	● Perceived enjoyment ● Perceived control	● Behavioral intention ● Word-of-mouth	Smart retail technology
Fazal-e-Hasan *et al.* (2021)	● Perceived compatibility ● Perceived risk	● Perceived novelty	● Intention to use	Smart retail technology
Roy *et al.* (2020)	● Perceived relative advantage ● Perceived complexity ● Perceived retailer support ● Perceived attractiveness	● Perceived enjoyment	● Behavioral intention	Smart retail technology
Roy *et al.* (2018)	● Perceived usefulness ● Superior functionality ● Perceived adaptiveness ● Store reputation		● Intention to use	
Nikhashemi *et al.* (2021)	● App interactivity ● The quality of the augmented reality ● App vividness	● App novelty	● Intention to use	Smart retailing

Table 1.
Previous studies on smart stores

grounded in HSAM to enable an understanding of utilitarian and hedonic motivations. The following sections present theories and models for the hypothesized relationships between smart retail technology interfaces, utilitarian and hedonic motivations and purchase intentions.

2.2 Hedonic system acceptance model

HSAM was developed based on technology acceptance model (TAM). TAM posits that user acceptance is determined by perceived usefulness and perceived ease of use. Perceived usefulness refers to "the degree to which an individual believes that using a particular system would enhance his/her job performance" and perceived ease of use refers to "the degree to which an individual believes that using a particular system would be free of effort" (Davis *et al.*, 1989).

Smart stores, in essence, are innovative applications of information technology because customers adopt smart retail technology to make purchases. As such, customers' purchase intentions have been explained in part by TAM Gefen *et al.* (2003a). Gefen *et al.* (2003b) integrated trust into TAM to examine customers' purchase intentions in online shopping. The results showed that purchase intentions are driven by the usefulness and ease of use of e-commerce websites. Based on TAM, Pavlou and Fygenson (2006) also found that perceived usefulness and perceived ease of use are important predictors of purchase intentions and purchase behaviors in e-commerce. Therefore, TAM is considered applicable for explaining customers' purchase intentions (Cheng *et al.*, 2012; Mohamed *et al.*, 2014; Shang and Wu, 2017).

However, TAM is merely applied to investigate utilitarian information systems related to productivity and task performance (Chang *et al.*, 2019). With the appearance of hedonic information systems that are linked to home and leisure activities, perceived enjoyment has been adopted to extend TAM (van der Heijden, 2004). Perceived enjoyment refers to "the extent to which the activity of using a particular system is perceived to be enjoyable in its own right, apart from anticipated performance consequences." In van der Heijden's model, perceived usefulness is described as utilitarian motivation, while perceived enjoyment is described as hedonic motivation. Thus, the proposed model is used to explain user acceptance of utilitarian- and mixed-motivation information systems.

Based on van der Heijden's model, Agarwal and Karahanna (2000) replaced perceived enjoyment with cognitive absorption consisting of five sub-dimensions, that is, control, curiosity, joy, focused immersion and temporal dissociation because cognitive absorption has more explanatory power in user acceptance than perceived enjoyment. Control refers to "the individual's perception of being in charge of the interaction", curiosity refers to "the degree to which the experience arouses an individual's sensory and cognitive curiosity"; joy refers to "the pleasurable aspects of the interaction that is described as fun and enjoyable rather than boring"; focused immersion refers to "the experience of total engagement where other attentional demands are essentially ignored"; and temporal dissociation refers to "the inability to register the passage of time while engaged in an interaction". Finally, cognitive absorption is a form of hedonic motivation that can be generated by the five sub-dimensions. As a result, the revised van der Heijden's model with cognitive absorption is called HSAM.

Since HSAM can be used to explain utilitarian and hedonic systems, this study employs this theory as a baseline to explain the antecedents of purchase intentions. Smart stores contain utilitarian and hedonic factors. For example, customers may make purchases because of low prices, efficiency and convenience; and they may also experience the pleasure of making purchases via smart retail technology. Accordingly, consumer motivation includes not only the goal of making purchases but also the pleasure of the purchasing process. Therefore, HSAM, which can measure utilitarian and hedonic motivations, is more appropriate and applicable for explaining the context of smart stores than traditional TAM and van der Heijden's model (Chang and Chen, 2021).

HSAM was originally proposed to describe user technology adoption in game software (Lowry *et al.*, 2012). As shopping in smart stores also involves hedonic motivation, to the best of our knowledge, this study is the first to extend and apply HSAM to explain both consumer motivations for shopping in smart stores. To investigate consumer motivation, HSAM integrates TAM, which investigates utilitarian information systems and cognitive absorption, which explains customers' hedonic motivation. Cognitive absorption, composed of five sub-dimensions is replaced by hedonic motivation, which describes customers' pleasant experiences, including control, curiosity, joy, focused immersion and temporal dissociation. Furthermore, perceived usefulness merely explaining goal-oriented shopping is replaced by utilitarian motivation, which is re-interpreted as functional benefits, including merchandise quality, merchandise price, location convenience, speed of shopping and product recommendation based on the situation of smart stores. The above factors create a formative second-order construct that drives customer shopping.

2.3 Situational factors

Situational factors proposed by Belk (1975) refer to situations and the recognized personal, environmental and social aspects of retail shopping, which explain customers' preferences, attitudes and intentions. Five situational factors influence customers' purchasing and shopping decisions: physical surroundings, social surroundings, temporal perspectives, task definition, and antecedent states. Physical surroundings are relevant to space factors, such as geographic or institutional location, sound and weather. Social surroundings refer to the presence of other persons, the characteristics of neighbors, and interpersonal interactions. Task definitions refer to the intention to select or shop and the expected user tasks. Temporal perspectives are related to time issues, such as time of day, the season of the year, and time constraints imposed by previous commitments. Antecedent states refer to momentary emotions or conditions that immediately precede the current situation (Belk, 1975).

Situational factors explain customer shopping in retail settings (Chen *et al.*, 2018; Collier *et al.*, 2015). Based on situational factors, Chen *et al.* (2018) investigated customers' intention to use self-service parcel delivery services in online retailing. They found that physical surroundings (i.e. location convenience), social surroundings (i.e. the need for human interaction), and temporal perspectives (i.e. perceived time pressure) influence consumer behavior. Collier *et al.* (2015) focused on customers' decisions to use self-service technology. The results showed that physical surroundings (i.e. location convenience), social surroundings (i.e. employee presence), task definition (i.e. order size), and temporal perspectives (i.e. wait-time tolerance) have a strong influence on customers' attitudes toward using the technology.

Since smart stores as well as traditional brick-and-mortar stores are both retail industries, they share similar situational factors. For example, in a retail context, customers care about merchandise quality and price (Baker *et al.*, 2002). Location convenience and waiting time for checkout also influence shopping decisions because the two facets are associated with customers' time and effort costs (Collier *et al.*, 2015; Seiders *et al.*, 2007). In addition, smart stores focus on interactions between customers and smart retail technology rather than interpersonal services. Thus, product recommendation is necessarily presented in a retail environment.

The 5 Ps of marketing proposed by McCarthy (1960), namely, product, price, promotion, place and people, are also popularly used to explain customers' purchasing decisions. Product refers to the items or services that a company offers to customers. Price refers to the cost that customers pay for the product or services. Promotion refers to the marketing activities used by a company to promote a product to customers. Place refers to the location where the product or services can be purchased. People refers to the salespersons who work for the company (McCarthy, 1960).

The five key elements have direct mappings to the situational factors selected by this study. Product and price are linked to merchandise quality and merchandise price offered by smart stores. Customers consider whether the quality and cost of the product meet their expectations when making purchases. Promotion is characterized as product recommendation based on consumer needs and preferences. Smart stores recommend products to customers for marketing campaigns. Place is characterized as location convenience and speed of shopping in smart stores. The factors involved in convenience determine how customers access and obtain products. In smart retail settings, traditional salespersons are replaced by smart retail technology. Thus, the effect of people is excluded from this study.

On the basis of situational factors and marketing management, this study proposes that situational factors can be categorized into physical surroundings (location convenience), social surroundings (product recommendation), temporal perspectives (speed of shopping) and task definition (merchandise quality and merchandise price). Because the situational factors are associated with the utilitarian motivation that captures functional benefits in smart stores, this study models utilitarian motivation as a formative second-order construct formed by the five situational factors.

3. Research hypotheses and model

On the basis of HSAM, customers' purchase intentions in smart stores are determined by utilitarian and hedonic motivations. From a utilitarian perspective, smart stores provide efficiency and effectiveness that support customer shopping. This study models utilitarian motivation as a formative second-order construct formed by five situational factors: merchandise quality, merchandise price, location convenience, speed of shopping, and product recommendation. From a hedonic perspective, smart stores enrich customer experiences and create positive sentiment via an immersive approach. There are strong correlations among the five sub-dimensions of cognitive absorption: control, curiosity, joy, focused immersion and temporal dissociation (Agarwal and Karahanna, 2000). Each dimension is highly correlated with a single factor: cognitive absorption. Thus, hedonic motivation is modeled as a reflective second-order construct comprised of five sub-dimensions.

Smart stores provide customers with both functional benefits and pleasant experiences through smart retail technology (Riegger *et al.*, 2021). Past research has also identified utilitarian and hedonic motivations as shopping goals that drive consumer behavior (Bridges and Florsheim, 2008; Chiu *et al.*, 2014; Lee and Wu, 2017; Jones *et al.*, 2006). Accordingly, if customers have greater utilitarian and hedonic motivations for the smart store, they will have greater purchase intentions toward the store. Therefore, we propose the following hypotheses:

H1. Utilitarian motivation positively affects purchase intentions.

H2. Hedonic motivation positively affects purchase intentions.

Perceived ease of use refers to the degree to which customers can freely use smart retail technology to complete purchases. This study conceptualizes perceived usefulness and cognitive absorption as utilitarian and hedonic motivations. Since perceived ease of use is the external variable of perceived usefulness and cognitive absorption (van der Heijden, 2004), we posit that perceived ease of use will influence utilitarian and hedonic motivations.

Customers can pay via smartphones or wearables, or walk out of the smart store without a checkout process. When customers encounter new technologies, they tend to worry about the success of learning the purchasing process (Roy *et al.*, 2020). If customers need to expend extra effort in learning and using it, then a poor shopping experience will reduce the effectiveness and pleasure of shopping. On the other hand, customers who perceive smart retail technology as easy to use are likely to increase their purchase intentions. Recent evidence suggests that the design of the purchasing process and the interface of smart retail technology influence consumer motivation (Adapa *et al.*, 2020; Lin, 2022; Roy *et al.*, 2018, 2020). Therefore, we propose the following hypotheses:

H3. Perceived ease of use positively affects utilitarian motivation.

H4. Perceived ease of use positively affects hedonic motivation.

H5. Perceived ease of use positively affects purchase intentions.

Utilitarian and hedonic motivations are consumer motivations for shopping in smart stores. This study postulates that utilitarian and hedonic motivations mediate the relationship between perceived ease of use and purchase intentions. According to HSAM, perceived usefulness and cognitive absorption mediate the relationship between perceived ease of use and behavioral intention (Lowry *et al.*, 2012). Thus, perceived ease of use serves as the antecedent of both consumer motivations and their behavioral intention. If customers find it easy to interact with smart stores, they will gain greater benefits when shopping. Smart stores allow customers to pay more quickly, improving their shopping efficiency and experiences (Fazal-e-Hasan *et al.*, 2021). As the interactions between customers and smart stores are reinforced by heightened ease of use, utilitarian and hedonic motivations further influence customers' purchase intentions. Therefore, we propose the following hypotheses:

H6. Utilitarian motivation mediates the relationship between perceived ease of use and purchase intentions.

H7. Hedonic motivation mediates the relationship between perceived ease of use and purchase intentions.

Merchandise quality refers to customers' evaluation of product quality. When making purchases, customers need to understand the features, advantages and benefits of the purchased product. Thus, the quality of the product must satisfy customers' needs and wants (Dodds *et al.*, 1991). Due to poor product quality, customers may choose an alternative channel to complete purchases. In other words, the better the product quality, the higher the purchase motivation. Prior research has also suggested a positive relationship between merchandise quality and customer satisfaction (Baker *et al.*, 2002; Zeithaml, 1988). Thus, merchandise quality will increase utilitarian motivation for shopping in smart stores. We propose the following hypothesis:

H8a. Merchandise quality positively affects utilitarian motivation.

Merchandise price refers to customers' perception of monetary costs for the product. Product price is directly linked to economic value (Dodds *et al.*, 1991). When making purchases, customers consider whether the price of the product is appropriate or lower than the market price. Thus, the low price of the product plays an important role in determining customer shopping. The lower the price perceptions, the higher the willingness to purchase (Baker *et al.*, 2002; Chiu *et al.*, 2014). The relationship between merchandise price and consumer value has been demonstrated (Baker *et al.*, 2002). Thus, merchandise price will enhance utilitarian motivation for shopping in smart stores. We propose the following hypothesis:

H8b. Merchandise price positively affects utilitarian motivation.

Location convenience refers to the perceived time and effort required to find a smart store. Location convenience is regarded as an important competitive factor in retailing and services and influences customer satisfaction and repurchase intentions (Jones *et al.*, 2003). As the distance to retail increases, consumer utility decreases because they spend extra resources accessing services. If the location of the smart store is too far for customers to access, customers must spend considerable time/effort patronizing the smart store. Customers are likely to choose an alternative store nearby. Previous studies have found the linkage between location convenience and shopping efficiency (Berry *et al.*, 2002; Chen *et al.*, 2018; Chiu *et al.*, 2014; Collier *et al.*, 2015). Thus, location convenience will increase utilitarian motivation for shopping in smart stores. We propose the following hypothesis:

H8c. Location convenience positively affects utilitarian motivation.

Speed of shopping refers to the time spent checking out in smart stores. Shopping efficiency is critical to driving customer shopping in smart stores (Collier *et al.*, 2015). Previous research has indicated that waiting time negatively influences customer shopping (Herrington and Capella, 1995; Durrande-Moreau and Usunier, 1999). Most customers opt to shop in smart stores to save checkout waiting time. If customers spend a great deal of time completing purchases, they will opt for an alternative efficient shopping environment (Chen *et al.*, 2018; Chiu *et al.*, 2014; Collier *et al.*, 2015; Palash *et al.*, 2022). The potential benefits for customers may be a quicker transaction, shopping efficiency and time savings. Thus, speed of shopping will heighten utilitarian motivation for shopping in smart stores. We propose the following hypothesis:

H8d. Speed of shopping positively affects utilitarian motivation.

Product recommendation refers to the ability of a smart store to promote products, services and the transactional environment to individual customers. Interactions with salespersons are replaced with interactions with smart retail technologies, such as personalized product information or promotions (Roy *et al.*, 2017). When customers pick up a product, smart stores may provide special discounts for the product and recommend related products through cross marketing techniques. Customers may also receive personalized recommendations based on their purchase history or personal preferences (Roe *et al.*, 2022). Personalized or customized services can help customers meet their shopping goals and tasks (Collier *et al.*, 2015; Riegger *et al.*, 2021; Srinivasan *et al.*, 2002). Thus, product recommendation will enhance utilitarian motivation for shopping in smart stores. We propose the following hypothesis:

H8e. Product recommendation positively affects utilitarian motivation.

4. Research methodology

4.1 Measurement development

The items for each construct were adapted from existing literature. Perceived ease of use was adapted from Davis *et al.* (1989). Purchase intention was adapted from Venkatesh *et al.* (2003). Utilitarian motivation was modeled as a second-order formative construct comprised of five sub-dimensions, namely, merchandise quality, merchandise price, location convenience, speed of shopping and product recommendation. Merchandise quality and merchandise price were adapted from Dodds *et al.* (1991). Speed of shopping was adapted from Seiders *et al.* (2007). Location convenience was adapted from Collier *et al.* (2015). Product recommendation was adapted from Srinivasan *et al.* (2002). Hedonic motivation was modeled as a second-order reflective construct composed of five sub-dimensions, namely, control, curiosity, joy, focused immersion and temporal dissociation. The items for the sub-dimensions were adapted from

Lowry *et al.* (2012). All items were measured using a seven-point Likert scale, ranging from strongly disagree (1) to strongly agree (7).

4.2 Data collection

This study used a purposive sampling approach to conduct data collection in China. China was chosen to investigate consumer behavior because China's smart retail market's size reached approximately 1.8 trillion yuan in 2022 (Ma, 2021). In particular, the number of smart shoppers reached 2.4 trillion. With the deployment of 5G networks, AI and IoT, China's well-known smart stores, including Jian 24, Cloudpick and take go, have introduced the same technology and business model as the world's leading smart store, Amazon Go. Jian 24 implemented several smart retail technologies, including computer vision and tracking mechanisms for customers and products, sensor fusion for purchase and self-checkout. Jian 24 owns hundreds of smart stores in China and helps other traditional brick-and-mortar stores to deploy smart retail technology. Smart stores allow customers to enter stores through face recognition, make purchases, and self-checkout for picked-up items.

Although no reports clearly indicate the number of consumers in smart stores, there are 842 million mobile online shoppers (Statista, 2022). Since consumers use mobile devices to make purchases, they can also do so via smart retail technology. Given the expected size effect of 0.3 and p-value of 0.5, the minimum sample size for SEM with 12 latent variables and 41 observed variables is computed to be 147 (Cohen, 1988; Soper, 2022; Westland, 2010). To ensure a representative sample of the population, this study ensured that all of the respondents who made purchases in smart stores. We cooperated with Jian 24 to randomly distribute online questionnaires to actual store customers. To encourage participation, the respondents who completed the questionnaire were offered a cash voucher of RMB$20. Finally, a total of 307 valid questionnaires were returned.

Appendix represents the demographic profiles of the respondents. There were 147 males (47.9%) and 160 females (52.1%). The majority of the respondents were between 18 and 35 years old (72.6%). The sampling percentage is similar to customer demographics published by Amazon (Kats, 2019), which found that 77% of respondents who prefer to a "just walk out" shopping experience are in the 18–34 age group. Most respondents had a bachelor's degree (66.1%). The sample showed that 48.1% of the respondents were professional, business personnel, and service industry personnel and 20.2% of the respondents had an income higher than RMB 10500. All of the samples make purchases in the smart store at least once a month.

4.3 Data analysis

This study used partial least squares (PLS) to conduct data analysis, which was chosen for the following reasons. First, PLS-SEM is suitable for examining complex models and exploratory research. Second, it relaxes the assumption of a normal distribution of sample data. Third, and most importantly, PLS-SEM is recommended by many statisticians when a research model involves higher-order constructs or formative constructs because the estimation results of PLS-SEM are accurate under such construct specifications (Becker *et al.*, 2012; Hair *et al.*, 2018). The present study develops a complex research model that explores consumer behavior in a novel multistage research context and contains 12 constructs including a formative second-order construct with five reflective first-order constructs and a reflective second-order construct with five reflective first-order constructs. Given the above discussions, Smart-PLS 3.0 was used to assess the measurement and structural models. For the measurement model, reliability, convergent validity and discriminant validity were evaluated. For the structural model, the paths and significance of all hypotheses were tested.

5. Results

5.1 Measurement model

PLS is used to assess reliability, convergent validity and discriminant validity. Table 2 shows that the factor loading for each item ranges from 0.76 to 0.96, which are higher than 0.7 (Hair *et al.*, 2019). Cronbach's α for all constructs range from 0.84 to 0.94, which are greater than 0.7. Composite reliability (CR) for all constructs range from 0.89 to 0.96, which are above 0.7. Average variance extracted (AVE) for all constructs range from 0.68 to 0.90, which are greater than 0.5 (Fornell and Larcker, 1981). Table 3 shows that the square root of the AVE of each construct is higher than the correlations between the construct and other

Construct	Item	Factor loading	Mean	S.D.	Cronbach's α	Composite reliability	AVE
Merchandise price (MP)	MP1	0.89	5.77	1.09	0.94	0.95	0.80
	MP2	0.90					
	MP3	0.93					
	MP4	0.87					
	MP5	0.89					
Merchandise quality (MQ)	MQ1	0.88	6.36	0.78	0.94	0.95	0.81
	MQ2	0.88					
	MQ3	0.92					
	MQ4	0.92					
	MQ5	0.89					
Location convenience (LC)	LC1	0.78	6.20	0.85	0.84	0.89	0.68
	LC2	0.80					
	LC3	0.85					
	LC4	0.86					
Speed of shopping (SS)	SS1	0.90	5.64	1.20	0.89	0.93	0.81
	SS2	0.92					
	SS3	0.89					
Product recommendation (PR)	PC1	0.92	6.10	1.00	0.94	0.96	0.89
	PC2	0.96					
	PC3	0.94					
Curiosity (CU)	CU1	0.96	5.46	1.38	0.92	0.96	0.93
	CU2	0.96					
Control (CT)	CT1	0.90	6.05	1.02	0.94	0.96	0.85
	CT2	0.94					
	CT3	0.94					
	CT4	0.90					
Joy	JOY1	0.91	6.22	0.91	0.90	0.94	0.84
	JOY2	0.95					
	JOY3	0.88					
Focused immersion (FI)	FI1	0.76	5.82	1.10	0.91	0.94	0.80
	FI2	0.93					
	FI3	0.93					
	FI4	0.94					
Temporal dissociation (TD)	TD1	0.93	5.76	1.26	0.85	0.93	0.87
	TD2	0.93					
Perceived ease of use (EOU)	EOU1	0.93	6.18	0.96	0.92	0.95	0.86
	EOU 2	0.92					
	EOU 3	0.94					
Purchasing intention (PI)	PI1	0.95	6.13	1.00	0.94	0.96	0.90
	PI2	0.96					
	PI3	0.94					

Table 2.
Reliability and convergent validity

Table 3.
Discriminant validity

Construct	MP	MQ	LC	SS	PR	CU	CT	JOY	FI	TD	EOU	PI
MP	0.90											
MQ	0.70	0.90										
LC	0.64	0.62	0.82									
SS	0.76	0.60	0.65	0.90								
PR	0.62	0.57	0.69	0.60	0.94							
CU	0.58	0.46	0.50	0.58	0.54	0.96						
CT	0.62	0.60	0.63	0.57	0.65	0.62	0.92					
JOY	0.63	0.63	0.74	0.57	0.72	0.55	0.80	0.91				
FI	0.62	0.55	0.62	0.60	0.65	0.80	0.76	0.76	0.89			
TD	0.67	0.61	0.58	0.66	0.63	0.70	0.75	0.69	0.79	0.93		
EOU	0.62	0.64	0.78	0.65	0.77	0.50	0.66	0.78	0.69	0.65	0.93	
PI	0.65	0.66	0.72	0.62	0.68	0.55	0.75	0.81	0.77	0.75	0.76	0.95

constructs (Fornell and Lacker, 1981). Table 4 shows that the heterotrait–monotrait (HTMT) values are less than 0.9 (Henseler *et al.*, 2016). Table 5 shows that the variance inflation factor (VIF) values range from 1 to 3.84, which are less than the threshold of 10

Table 4.
Heterotrait–monotrait ratio (HTMT)

	MP	MQ	LC	SS	PR	CU	CT	JOY	FI	TD	EOU	PI
MP												
MQ	0.74											
LC	0.72	0.69										
SS	0.83	0.65	0.75									
PR	0.66	0.61	0.78	0.65								
CU	0.62	0.50	0.57	0.64	0.59							
CT	0.66	0.64	0.71	0.62	0.69	0.67						
JOY	0.68	0.68	0.84	0.64	0.79	0.60	0.86					
FI	0.67	0.59	0.71	0.67	0.70	0.88	0.82	0.83				
TD	0.75	0.68	0.69	0.76	0.71	0.79	0.84	0.79	0.90			
EOU	0.66	0.69	0.87	0.71	0.83	0.55	0.71	0.85	0.75	0.73		
PI	0.68	0.70	0.81	0.68	0.72	0.59	0.80	0.88	0.83	0.84	0.82	

Table 5.
Variance inflation factor values

	CU	CT	JOY	FI	TD	EOU	PI	HB	UB
MP									3.19
MQ									2.29
LC									3.02
SS									2.75
PR									2.76
CU									
CT									
JOY									
FI									
TD									
EOU							3.06	1.00	3.74
PI									
HM	1.00	1.00	1.00	1.00	1.00		3.15		
UM							3.84		

Note(s): UM (Utilitarian motivation), HM (Hedonic motivation)

(Hair *et al.*, 1992; Mathieson *et al.*, 2001). Thus, this study supports the convergent validity and discriminant validity of the measurement model.

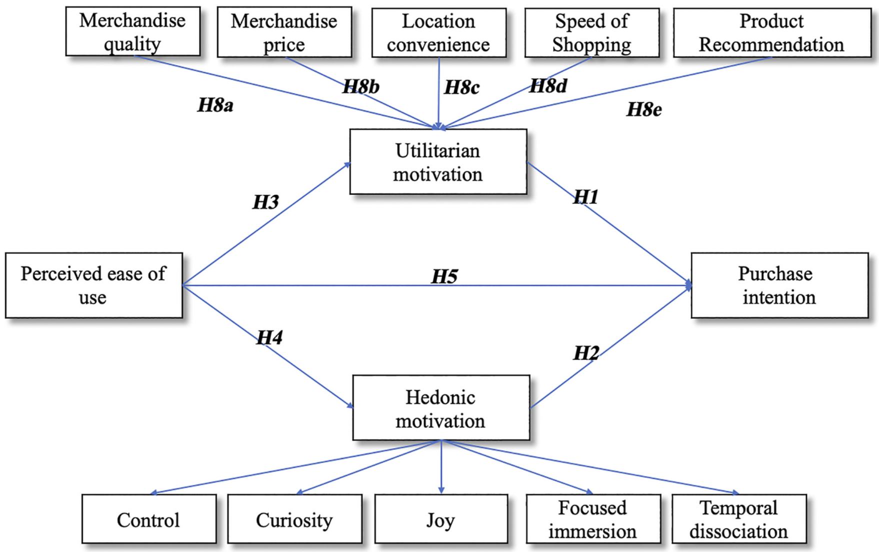
Utilitarian motivation is modeled as a formative second-order construct, which is measured by observed variables for merchandise price, merchandise quality, speed of shopping, location convenience and product recommendation. As shown in Table 3, the path coefficients of the five first-order constructs are not highly correlated among themselves (value < 0.8), indicating the discriminant validity of the five constructs as formative constructs of utilitarian motivation (Hair *et al.*, 2012).

Hedonic motivation is modeled as a reflective second-order construct, which is measured by observed variables for control, curiosity, joy, focused immersion and temporal dissociation. As shown in Figure 1, the five first-order constructs on hedonic motivation are significant ($p < 0.05$), establishing the nomological validity of the reflective model. R^2 value for the first-order constructs is higher than 0.5, indicating that the five constructs explain the significant variance in hedonic motivation (Hair *et al.*, 2012).

5.2 Structural model

PLS is used to assess the significance of the path coefficient for hypostasized relationships. As shown in Figure 2, utilitarian motivation ($\beta = 0.212$, $p < 0.01$), hedonic motivation ($\beta = 0.518$, $p < 0.001$) and perceived ease of use ($\beta = 0.193$, $p < 0.01$) positively influence purchase intentions, which supports H1, H2 and H5. R^2 for purchase intentions is 74.9%. Perceived ease of use positively influences utilitarian motivation ($\beta = 0.853$, $p < 0.001$) and hedonic motivation ($\beta = 0.751$, $p < 0.001$), supporting H3 and H4. R^2 values for utilitarian and hedonic motivations are 72.8 and 56.4%, respectively.

Regarding the formative second-order construct, merchandise quality ($\beta = 0.240$, $p < 0.001$), location convenience ($\beta = 0.413$, $p < 0.001$), speed of shopping ($\beta = 0.142$, $p < 0.01$) and product recommendation ($\beta = 0.380$, $p < 0.001$) positively influence utilitarian



H6: Perceived ease of use→Utilitarian motivation→Purchase intentions
H7: Perceived ease of use→Hedonic motivation→Purchase intentions

Figure 1.
Research model

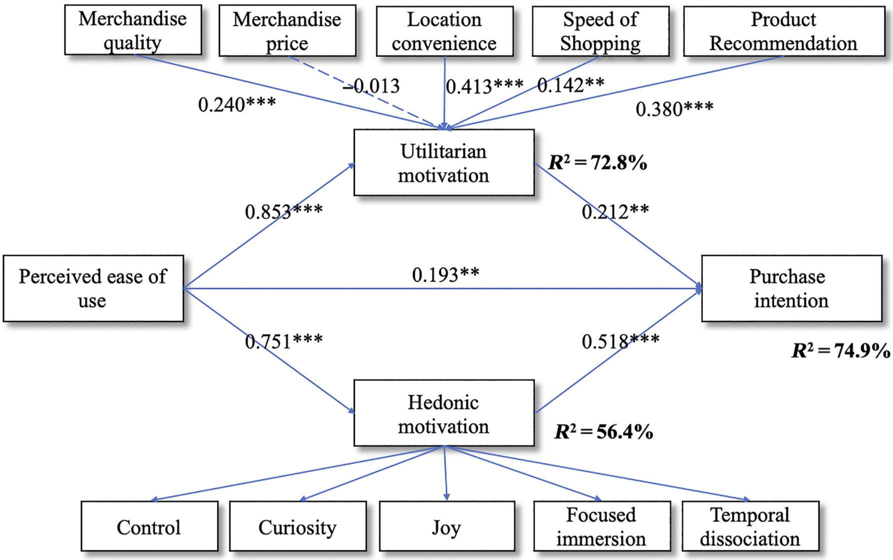


Figure 2.
Results

motivation. However, contrary to expectations, merchandise price ($\beta = -0.013, p > 0.05$) has no significant impact on utilitarian motivation. Thus, H8a, H8c, H8d and H8e are supported.

As suggested by Hair *et al.* (2022), this study conducts mediation analysis with 5,000 bootstrapping samples and a 95% confidence level. As shown in Table 6, all indirect effects are significant, supporting H6 and H7. Perceived ease of use has a significant effect on purchase intentions through utilitarian and hedonic motivations.

5.3 Robustness check

Endogeneity is examined by following the guideline proposed by Hult *et al.* (2018), who recommended the Gaussian copula approach in PLS-SEM. The non-normal distribution of the variables (i.e. perceived ease of use, utilitarian motivation and hedonic motivation) should be verified before implementing the Gaussian copula approach. After running the Kolmogorov–Smirnov tests with Liffiefors correction on the latent variable scores of these variables, the results indicate that none of these variables' scores are normally distributed. The Gaussian copula approach was then performed with the R codes contributed by Hult *et al.* (2018). The results reveal significant effects of the copulas for utilitarian and hedonic motivations on purchase intentions, implying the possibility that these two independent variables being endogenous. With the remedy of the control variables approach (Hult *et al.*, 2018), the model was unable to further explain the source of endogeneity.

In this situation, as suggested by Hult *et al.* (2018), researchers should report the results found by the Gaussian copula approach, while acknowledging the endogeneity origin remains unknown in their studies. In our case, although the endogeneity origin could not be

Table 6.
Mediation test

Hypothesis	Std. Beta	95% bias corrected confidence internal	Results
H6: EOU→UM→PI	0.181**	[0.304, 0.489]	Supported
H7: EOU→HM→PI	0.389***	[0.087, 0.295]	Supported

identified at the moment, the whole model estimations with the Gaussian copulas approach do not change any result inferences derived from the original research model. Therefore, endogeneity is not a critical issue that undermines the reliability of the results of the proposed model.

6. Discussion

This study utilizes HSAM to propose a research model including utilitarian and hedonic motivations to investigate customers' purchase intentions in smart stores. The findings of this study show that purchase intentions are determined by utilitarian and hedonic motivations and perceived ease of use. In addition, perceived ease of use influences utilitarian and hedonic motivations, which in turn, determine purchase intentions. Functional benefits and pleasant experiences of purchases and the interaction with smart retail technology in smart stores would increase customers' purchase intentions. Consistent with the findings in e-commerce (Chiu *et al.*, 2014; Lee and Wu, 2017; Nikhashemi *et al.*, 2021), this study identifies the roles of utilitarian and hedonic motivations in affecting purchase intentions in smart retail settings.

This study identifies the constituents of utilitarian motivation affecting purchase intentions. The proposed situational factors, that is, merchandise quality, location convenience, speed of shopping and product recommendation, are significant sub-dimensions of utilitarian motivation. In addition to the utilitarian factors of traditional brick-and-mortar stores, motivation also considers functional benefits derived from smart stores with innovative technologies, including convenient access, high shopping efficiency, and personalized product recommendation. Although product price plays an important role in the 5Ps of marketing, we do not find that merchandise price significantly influences utilitarian motivation. A possible reason could be that smart stores and traditional brick-and-mortar stores adopt the same pricing method. Since customers perceive that the price of the purchased merchandise is similar to that of other alternative stores, they do not obtain any economic benefits from smart stores. Thus, there is an insignificant relationship between merchandise price and utilitarian motivation.

This study identifies the constituents of hedonic motivation affecting purchase intentions. Different from previous research that adopted only a single construct to describe customers' pleasant experience (Adapa *et al.*, 2020; Roy *et al.*, 2017, 2020; Nikhashemi *et al.*, 2021), hedonic motivation in this study is composed of control, curiosity, joy, focused immersion and temporal dissociation. The findings of this study show that the five sub-dimensions are highly correlated and consistent with the concept of cognitive absorption (Lowry *et al.*, 2012), which has been examined in the contexts of online learning websites (Saadé and Bahli, 2005), mobile devices (Wakefield and Whitten, 2006) and the web (Agarwal and Karahanna, 2000). Therefore, customers who perceive higher hedonic motivation composed of the five first-order constructs for the smart store are willing to make purchases at the store.

The results provide support for the previously employed theories, including HSAM, situational factors and cognitive absorption. The proposed theoretical model links consumer motivation and purchase intentions. Consumer motivation draws upon functional benefits and pleasant experiences. Finally, we identify that merchandise quality, location convenience, speed of shopping and product recommendation constitute utilitarian motivation, which corroborates the 5Ps of marketing and situational factors. From a hedonic point of view, control, curiosity, joy, focused immersion and temporal dissociation constitute hedonic motivation. In addition, this study provides empirical evidence for the mediating effects of both consumer motivations in the entire shopping experience.

7. Implications for theory and practice

7.1 Implications for theory

HSAM integrates TAM, which mainly investigates utilitarian information systems and cognitive absorption in accounting for customers' hedonic motivation, to explain the factors influencing technology adoption. Since customers in smart stores must not only adopt new technology but also make purchases in new environments, this study posits the extended HSAM to explain consumer motivation for shopping in settings equipped with new technologies. The results show that perceived ease of use influences purchase intentions through utilitarian and hedonic motivations. By replacing perceived usefulness and perceived enjoyment with utilitarian and hedonic motivations, the model comprehensively represents consumer motivation driving behavioral intentions and has better explanatory power than the traditional adoption model (Lowry *et al.*, 2012). Future research is encouraged to apply the proposed model to study the effect of both consumer motivations in other shopping settings.

Prior studies have largely focused on the adoption of smart retail technology (Adapa *et al.*, 2020; Aw *et al.*, 2021; Fazal-e-Hasan *et al.*, 2021; Roy *et al.*, 2017; Roy *et al.*, 2018). However, a successful smart retail business requires customers to make purchases, not just accept new technologies. Apart from the traditional adoption model, this study provides insights into customer shopping in smart stores. To the best of our knowledge, this study is the first to examine how consumer motivation influences purchase intentions in smart stores. The findings not only confirm that both motivations lead to purchase intentions (Chiu *et al.*, 2014) but also highlight the importance of hedonic motivation ($\beta = 0.518$), as its path coefficient is more than twice that of utilitarian motivation ($\beta = 0.212$). Future research is encouraged to investigate the importance of hedonic motivation in other shopping settings.

Although the various components of utilitarian motivation have been studied before (Adapa *et al.*, 2020; Roy *et al.*, 2017, 2018), they were treated as isolated concepts. In this study, an integrated utilitarian construct is proposed and validated by fusing the 5Ps of marketing and situational factors. This study models utilitarian motivation as a formative-second order construct comprised of merchandise price, merchandise quality, location convenience, speed of shopping and product recommendation. The results show that four of the five sub-dimensions have a significant impact on utilitarian motivation. The four components are by no means complete; therefore, future research can enhance the findings by supplementing other components of utilitarian motivation.

Hedonic motivation reflects five different pleasant experiences in smart stores: control, curiosity, joy, focused immersion and temporal dissociation. In line with the concept of cognitive absorption proposed by Agarwal and Karahanna (2000), this study models hedonic motivation as a reflective construct composed of five first-order constructs. The results show that the five sub-constructs are strongly correlated. Although previous studies on smart stores have focused mainly on utilitarian motivation (Adapa *et al.*, 2020; Fazal-e-Hasan *et al.*, 2021; Nikhashemi *et al.*, 2021; Roy *et al.*, 2017, 2020), our findings imply that purchase intentions are influenced more by hedonic motivation than utilitarian motivation. Future research should emphasize not only utilitarian motivation but also hedonic motivation.

This study provides evidence that utilitarian and hedonic motivations mediate the relationship between perceived ease of use and purchase intentions. The findings corroborate the traditional adoption model (e.g. TAM and van der Heijden's model), which posited that perceived ease of use is the antecedent of perceived usefulness and perceived enjoyment. Our study further demonstrates that consumer motivation plays a mediating role in smart retail settings. Future studies are encouraged to verify the findings in other shopping settings.

7.2 Implications for practice

This study offers several implications for practitioners to better understand and improve consumer motivation in smart stores. According to an Amazon report, 48% of consumers believe that smart technology would entice them to shop at smart stores, and 43% of the participants further indicated that they prefer checking out with smart technologies rather than waiting in a checkout at traditional brick-and-mortar stores (Kats, 2019). Thus, utilitarian and hedonic motivations driven by smart stores have a positive influence on purchase intentions. Perceived ease of use of smart technology and the purchasing process also directly influences utilitarian and hedonic motivations.

From the perspective of utilitarian motivation, retailers should provide functional benefits that are characterized by good product quality, convenient access, high shopping efficiency and personalized product recommendation. The path coefficient of location convenience is the highest ($\beta = 0.413$) among utilitarian motivations. The finding echoes a survey indicating that 75% of consumers are likely to shop in a smart store if they conveniently pass by (shorr, 2018). Thus, smart stores should be located in areas with high traffic, such as the lobbies of business buildings, main entrances of communities and transportation hubs. As merchandise quality significantly affects utilitarian motivation, retailers should ensure the quality and freshness of the products sold and even ensure the availability of certain brands to attract customers. According to a report (shorr, 2018), more than 25% of customers are likely to shop in smart stores if they do not have to wait in line at a checkout. This point was confirmed by this study. Because of the absence of salespersons, strengthening a smooth check-out process is essential for the enhancement of shopping efficiency. Smart stores should install sensors and cameras tracking all customers and products to identify picked-up items by each customer. Thus, stores can charge customers while they are on the way out. Since personalized product recommendation is an important factor, retailers should invest more in recommendation systems because product recommendations encourage customers to stay in stores longer and to examine needed products more thoroughly. Thus, smart stores should also proactively provide timely personalized promotions and recommendations by analyzing customer profiles, transactional history and picked-up items. An intriguing point is that this study finds merchandise price to be an insignificant utilitarian factor. This implies that customers are less sensitive to price than to other factors. Therefore, retailers may not need to emphasize cost control at this stage.

Another important finding is that hedonic motivation has a greater impact on purchase intentions than utilitarian motivation. Thus, retailers should prioritize creating a pleasant store atmosphere and an enjoyable shopping environment, which entices customers to stay longer and ignore time and effort expenditures in smart stores. In addition, retailers should strive to enhance novel experiences while customers shop in stores. Smart stores can introduce purchasing processes, guide operations and facilitate transaction completion through innovative technologies, such as artificial intelligence or virtual reality, as pleasant experiences motivate customers to increase shopping time, make unplanned expenditures and be more willing to make purchases.

Perceived ease of use plays a pivotal role in purchase intentions in smart stores. The construct assists both utilitarian and hedonic motivations in contributing to purchase intentions. Retailers should pay special attention to simplifying the purchasing process and lowering interface complexity to increase the effects of utilitarian and hedonic motivations. In particular, to attract potential new customers, smart stores should simplify the registration process to lower technical barriers and encourage them to patronize stores. For existing customers, smart stores should adopt face recognition and image recognition to simplify the entire purchasing process, including entering and exiting the stores and charging for picked-up items.

8. Conclusion and limitations

This study focuses on customers' purchase intentions in smart stores, and represents a comprehensive view of utilitarian and hedonic motivations in examining the determinants of purchase intentions. The results show that perceived ease of use and utilitarian and hedonic motivations influence purchase intentions and the direct and indirect effects of perceived ease of use on purchase intentions. In addition, we model utilitarian and hedonic motivations as second-order constructs. The former is a formative second-order construct comprised of merchandise price, merchandise quality, location convenience, speed of shopping and product recommendation. The latter is a reflective second-order construct composed of control, curiosity, joy, focused immersion and temporal dissociation. Given that hedonic motivation has better explanatory power than utilitarian motivation, we provide practical suggestions for retailers to improve consumer motivation and developing a competitive advantage.

This study has several limitations that provide opportunities for further research. First, although we strive to include comprehensive components from the perspective of utilitarian and hedonic motivations, future research could examine whether other components, such as merchandise brands and store brands, can be added to utilitarian motivation. Second, although the extended HSAM with situational factors and cognitive absorption can explain utilitarian and hedonic effects of grocery shopping, applying the proposed model to other industries may require extra caution as the utilitarian motivations may be different for other industries. For example, the car washing industry may not have real-time recommendations, and consumers may put less priority on hedonic motivations in health industries, such as patients utilizing smart health. Third, the survey design was cross-sectional. Future research can be undertaken based on field experiments and secondary data to examine repurchase behavior. Fourth, because this study collected data from customers who had made purchases in smart stores, our results may be influenced by self-selection bias. Moreover, because the data were collected by convenience sampling, the generalizability of the results may be constrained. Future research could conduct sampling in a more systematic way to ensure that the sampling data represent the entire population. Last, as this study investigated purchasing motivation and behavior in China, cultural differences could play a role in determining consumer motivation and behavior. Future research is encouraged to collect data from other countries for cross-cultural comparisons.

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Appendix

Measure	Items	Frequency	Percent (%)
Gender	Male	147	47.9
	Female	160	52.1
Age	18–25 years	74	24.1
	26–35 years	149	48.5
	36–45 years	57	18.6
	46–55 years	23	7.5
	56–65 years	4	1.3
Education	Senior high school	49	16.0
	University	203	66.1
	Master	47	15.3
	Doctor	8	2.6
Career	Government personnel and State-owned enterprise personnel	50	16.3
	Professional	67	21.8
	Staff	11	3.6
	Business personnel and service industry personnel	64	20.8
	Personnel in agriculture, forestry, animal husbandry, fishery, water conservancy	1	0.3
	Production operator	4	1.3
	Soldier	3	1.0
	Others	107	34.9
Income (monthly)	Less than RMB 1500	24	7.8
	RMB 1501–3000	18	5.9
	RMB 3001–4500	53	17.3
	RMB 4501–6000	52	16.9
	RMB 6001–7500	29	9.4
	RMB 7501–9000	33	10.7
	RMB 9001–10500	36	11.7
	More than RMB 10500	62	20.2
Times of purchase at the smart store (monthly)	Less than 1 time	125	40.7
	1 time	107	34.9
	2 times	35	11.4
	3 times	13	4.2
	4 times	8	2.6
	5 times	6	2.0
	More than 5 times	13	4.2

Table A1.
Profile of respondents

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