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Factors Influencing Consumer Purchasing Behaviour of Intelligent Connected Vehicles

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ABSTRACT

Energy conservation and emission reduction in the transportation sector are crucial for tackling global climate change. With advancements in electric vehicle (EV) technology and intelligent connected features, the factors influencing consumer purchase behaviour have evolved. Intelligent connected vehicles (ICVs) are gaining significant market attention, with many new ICV brands emerging in the Chinese market in recent years. Despite this growth, research in this area remains limited. This study uniquely contributes to the field by examining how intelligent connected features and brand equity influence ICV purchase behaviour. Using the UTAUT model and partial least squares structural equation modelling (PLS-SEM), the study reveals that performance expectancy, effort expectancy, social influence, intelligent connected features, and brand equity all positively impact consumer purchase behaviour. Notably, the analysis highlights the strong role of intelligent connected features and brand equity in shaping consumer purchasing behaviour of ICVs, offering valuable insights for the development of the ICV industry.

JEL Classification: D12, M31, O33

Keywords: Brand equity; Intelligent connected vehicle; Intelligent connected features; Purchase behaviour; UTAUT

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INTRODUCTION

Approximately 55% of total consumption in the global transport sector has been projected to consist of liquid fuels by 2050, which is similar to the percentage observed in 2015. The G20 countries (including China and the United States) collectively contributed 75% of global greenhouse gases (GHG) emissions in 2020 (UNEP, 2022). China possesses a large population, which can result in high energy consumption. The travel and freight demand in China is also experiencing a significant surge, surpassing that of other organisation for economic co-operation and development (OECD) countries. Simultaneously, the oil demand growth of China is the highest in the world, which is twofold that of India (second rank) (Wu et al., 2022).

The EVs promotion and adoption are crucial measures to reduce carbon emissions in the transportation sector. These EV sales are accelerating globally, with the Chinese and European markets achieving new records. The International Energy Agency reported that the EV sales volume in 2022 increased by over double compared to the previous year, reaching 6.6 million units (International Energy Agency, 2022). These EV types included battery electric vehicles and plug-in hybrid EVs. Consequently, the total number of EV users worldwide exceeded 16.5 million. Although the global transportation field only contains a small portion of EVs, certain countries have successfully promoted them in their transportation systems (Choi et al., 2018).

As EV adoption grows, the integration of advanced technologies include 5G and the Internet of Things (IoT) is enhancing their capabilities (Li et al., 2018). One key application of these technologies is the development of intelligent connected vehicles (ICVs), which leverage 5G-enabled IoT connectivity to offer smarter, more responsive driving experiences. ICVs, often built on EV platforms, utilize intelligent connected features as a core feature (Ullah et al., 2021). This enables EVs to function as smart devices, providing seamless communication, real-time data exchange, and enhanced convenience for users (Guang et al., 2018). The advancement of IoT technology also offers essential technical assistance for ICVs, functions as the foundation for the intelligent connected features of ICVs, and acts as the support system that guarantees the seamless operation of these networks (Hijjawi et al., 2024). As such, the combination of EV technology and IoT-powered intelligent connected features is shaping the future of transportation, not only reducing emissions but also improving the driving experience through cutting-edge technological integration.

This study examined the consumers' perspectives concerning the ICV industry. The factors impacting consumer purchase behaviour of ICVs and the influence of the intelligent connected features regarding consumer acceptance with decision-making were determined. The ICV industry has focused primarily on technological advancement, sometimes neglecting market and consumer research (Kim and Cho, 2024). Nevertheless, this excessive focus on technology has disregarded the critical analysis of business models and consumer insights, which are vital for achieving sustainable growth and market competitiveness (Chesbrough, 2010). A study by Wang et al. (2022) demonstrated that many studies were primarily concerned with addressing technological and economic models. Furthermore, these studies neglected social policies and user attitudes. Even though technical issues would not result in disruptive changes in behaviour patterns, the user's complexity should also be emphasised and understood. Currently, China possesses a substantial amount of ICVs and intelligent connected technology-related studies. Nevertheless, studies on brands and consumers are essential for ICVs to penetrate the market effectively (Larson et al., 2014). Therefore, overemphasising technology while disregarding the fundamental nature of ICVs as a consumer product could lead to lower comprehension of the corresponding market, brands, and consumers.

While prior studies have explored the environmental impact of EVs and consumer acceptance of autonomous driving features (Asadi et al., 2022; Damaj et al., 2021; Nazari et al., 2018) research on intelligent connected features (ICFs) within intelligent connected vehicles (ICVs) remains limited. Ullah et al. (2021) identified ICFs as key factors in consumer engagement but did not examine their direct impact on purchase behavior. Additionally, existing studies have largely approached ICV adoption from a corporate and technological perspective rather than a consumer-centric one (Golbabaei et al., 2020).

Brand equity plays a crucial role in shaping consumer trust and purchase decisions, especially in emerging industries like ICVs (Jiang et al., 2021). While Chinese ICV brands have gained significant global market share (Li et al., 2020), the influence of brand equity on consumer purchase behavior remains underexplored, particularly concerning consumer perceptions and the "origin effect" (Elhaoussine et al., 2023). Moreover, many studies rely on purchase intention rather than real-world purchase behavior, limiting practical insights due to low ICV adoption rates (Salari, 2022). Given the high ICV adoption in China, this study focuses on actual purchasing behavior rather than intention, offering a more practical understanding of consumer decisions.

To bridge these gaps, this study examines how intelligent connected features and brand equity influence consumer purchase behavior of ICVs in China. By integrating the Unified Theory of Acceptance and Use of Technology (UTAUT), this research provides a comprehensive perspective on consumer decision-making in the rapidly evolving Chinese ICV market.

LITERATURE REVIEW

Electric Vehicles (EVs) and Intelligent Connected Vehicles (ICVs)

The EV design is introduced into the market in response to the increased environmental pollution and policies implemented by certain countries (Rohde and Muller, 2015). Hence, improved battery technology and increased research capabilities in recent years have led to the development of various EVs, providing consumers with more options. Multiple EV definitions have been recorded in the Chinese EV market based on different technologies and power source. Additional explanations, industry-standard, and other authorised EV types for sale is also included in new energy vehicles.

An ICV is a vehicle with advanced sensors, controllers, and actuators. These vehicles utilise novel technologies such as information communication, the Internet, big data, cloud computing, artificial intelligence, and partially or fully autonomous driving functions. Consequently, these vehicles transform into a "smart mobile space", representing the next generation of cars (Gersdorf et al., 2020; Jin and Jing, 2020). An ICV is an intelligent connected vehicle (Ullah et al., 2021).

Intelligent Connected Features and Consumer Purchase Behaviour

Ullah et al. (2021) assessed the consumer engagement of a company with EVs. The study defined ICVs as EVs which containing intelligent connected features, presenting several intelligent connected features for the users. Other factors affecting consumers' purchasing behaviour were also suggested in the study.

Even though multiple studies have been conducted on the environmental impact of EVs, limited research concerning the intelligent connected features of ICVs has been observed (Asadi et al., 2022). Previous consumer acceptance-related studies of autonomous vehicles mainly concentrated on their autonomous driving features (Damaj et al., 2021; Golbabaei et al., 2020a; Nazari et al., 2018). In contrast, these studies neglected the broader ICV features due to rapid ICV technological advancements and inadequate delineation of ICV features (Acharya and Mekker, 2022; Guo et al., 2021).

Ullah et al. (2021) validated the importance of consumer engagement with ICVs. The study referred to this process as EVs equipped with intelligent connected features. Nonetheless, a significant research gap was present about the correlation between various intelligent connected features in ICVs and consumer purchase behaviour.

Brand Equity and Its Influence on Consumer Purchase Behaviour

Brand equity plays a crucial role in influencing consumer purchase decisions, particularly in emerging sectors like ICVs (Jiang et al., 2021). Research shows that a strong brand image can significantly enhance consumer confidence in adopting new technologies, including ICVs. Therefore, brand equity is a vital factor to consider when examining purchasing behavior in this domain.

Emerging ICV brands (such as Tesla and NIO) have recently prioritised technological advancements (Jiang et al., 2021). Chinese brand ICVs represented over 40% of the global sales of the top 10 ICVs in December 2019 (Li et al., 2020). This percentage reached about 70% in April 2018, which suggested that Chinese brand ICVs possessed significant sales volume based on statistics. Nonetheless, consumers can present unfavourable perceptions of Chinese brands due to the origin effect (Elhaoussine et al., 2023). This perception poses a constraint for Chinese ICV brands.

The precise influence of Chinese ICV brand equity on consumers’ purchasing behaviour is also poorly understood. A significant research gap concerning how brand equity of Chinese ICVs affects consumers’ purchasing behaviour is observed.

Consumer Experience and Purchase Behaviour in ICVs

A study by Graham-Rowe et al. (2012) examined the consumers' acceptance in the United Kingdom (UK), which acquired some positive responses from mainstream consumers. The study also demonstrated that these mainstream consumers encountered certain concerns in purchase behaviour.

Meanwhile, certain studies highlighted that experienced consumers were more likely to be confident in acquiring EVs (Larson et al., 2014). Hence, further ICV studies concerning consumers' purchase behaviour change are necessary due to technological advancements and the availability of information on ICVs in recent years.

Research Gaps in Prior Studies on ICV Purchase Behaviour

A study by Golbabaei et al. (2020) primarily examined the technological development in this industry, emphasising the functionality of a single technology (autonomous driving system). The previous study investigated the corporate perspective other than the consumer perspective to enable the industry-related company to monitor their consumer's purchasing behaviour and develop their product and technology. This previous study finding contributed to the ICV industry, focusing on the changing situation from the consumer's perspective.

Although the consumer behaviour assessment using purchase intention is unreliable, many purchase intention-related studies have been reported without using real adopters with ICVs driving experience. This observation is attributed to the low adoption of ICVs, rendering it challenging to recruit actual adopters (Salari, 2022). Therefore, real adopters with ICV driving experience should be utilised for further studies. Given the high ICV usage rate in the Chinese market, this study prioritised examining purchase behaviour rather than purchase intention for improved practicality.

The Unified Theory of Acceptance and Use of Technology (UTAUT)

The UTAUT is a sophisticated framework primarily employed to measure individuals' acceptance of new technologies and information systems in a company (Venkatesh et al., 2003). Considering that UTAUT is a technology acceptance model, the framework is formed by integrating other behaviour prediction models. This model is also extended to different fields and research objects, including its usage in emerging technological fields and user acceptance investigation of novel technologies (Jahanshahi et al., 2020; Sun et al., 2009). A study by Qu et al. (2022) introduced UTAUT as a primary research model to investigate the factors potentially impacting consumer use of electronic cash in China and found that the use intention have significant impact to the use behaviour.

The UTAUT model is well-suited for this study as it provides a comprehensive framework for understanding consumer purchasing behaviour of intelligent connected vehicles (ICVs), incorporating factors like performance expectancy, effort expectancy, social influence and that go beyond the technology acceptance model (TAM) (Venkatesh et al., 2003). Its inclusion of technical experience and adaptability to local contexts, such as the consumer purchasing behaviours in China, makes it especially relevant for analysing the rapidly growing ICV market. Prior research, like Sohn and Kwon (2020), shows UTAUT's superiority over TAM in predicting behavioural for advanced technologies, making it an ideal fit. Additionally, UTAUT's flexibility allows the study to explore how brand equity and intelligent connected features' influence on consumer purchasing behaviours.

This study applied the UTAUT in the ICV industry and expanded upon potential factors influencing consumer behaviour. Likewise, a study by Cai et al. (2023) extended the UTAUT model to evaluate user acceptance of autonomous buses. Overall, these studies could demonstrate the applicability of UTAUT in analysing purchase behaviour and its adaptability to various technologies or products. A traditional UTAUT model commonly retains four original UTAUT mechanisms, in which an external mechanism is then incorporated (Tamilmani et al., 2021). Nevertheless, this study enhanced the UTAUT model by including the research objectives and ICV characteristics while maintaining its relevant constructs. The proposed study framework was built upon the UTAUT model by incorporating a new mechanism, which involved applying the UTAUT model for further research (Tamilmani et al., 2021; Venkatesh et al., 2016).

In the UTAUT model, Facilitating Conditions refer to the degree of one's belief that either the technology itself or the supporting organization can assist in the use of the system (Venkatesh et al., 2003).

However, research by Venkatesh and Davis (2000) identified Facilitating Conditions as an indirect construct when various models were integrated into the UTAUT framework. Their study found that Effort Expectancy fully mediated the effects of Facilitating Conditions, suggesting that Facilitating Conditions may not directly influence behavioral intention when other key predictors are present.

This finding implies that in models like theory of planned behaviour, where effort Expectancy is excluded, Facilitating Conditions might serve as a significant predictor of behavioral intention. However, when both performance expectancy and effort expectancy are theoretically considered, as they are in the UTAUT model, the role of Facilitating Conditions becomes insignificant in predicting behaviour (Venkatesh and Davis, 2000; Venkatesh et al., 2003; Fleury et al., 2017).

This insight supports the decision to exclude facilitating conditions in contexts where both performance and effort expectancy are robust predictors of technology adoption, as is the case in this study. In addition, this study is targeted at consumers of ICVs in China’s first-tier cities, so it is reasonable to exclude this factor. These regions already have a well-developed ICVs infrastructure and advanced technologies such as 5G and the Internet of Things, which provide a technical foundation for the popularization of ICVs. Therefore, consumers in these regions are unlikely to encounter major barriers related to infrastructure or technical support, making convenience less important to their purchasing behaviour.

Brand Equity Model

Brand equity is a term used to describe the financial perspective of a brand. This value measures price or cashflow yield (Swait́ et al., 1993). Conversely, the brand equity evaluation has transitioned to the consumer perspective due to the market and company operation changes. Several measurements are included in this valuation, such as loyalty, awareness, perceived quality, perceived value, and image (Aaker, 1996; Keller, 2001). This approach enables the brand equity assessment from the consumer perspective without being restricted to financial indicators. Thus, this study examined brand equity from the consumer perspective to ascertain its impact on consumer purchasing behaviour. A study by Aaker (1996) proposed a brand equity model containing four measurements: brand awareness, brand loyalty, perceived quality, and brand association.

Performance Expectancy and Purchase Behaviour of ICVs

A study by Bu et al. (2021) denoted performance expectancy as individuals' belief in using a specific technology that could facilitate performance improvement. The study emphasised the significance of performance expectations in shaping users' adoption and influencing users' acceptance and technology use (Bu et al., 2021; Venkatesh et al., 2003). Similarly, a study by Kim et al. (2022) verified that performance expectancy directly impacted consumers' perception of the functions and characteristics of a specific technology. On the contrary, the factors influencing the users' final behavioural intentions were not the decisive factor.

Another study by Osswald et al. (2012) reported the development of information technology in vehicles and the drivers' acceptance of the vehicle’s technology. The vehicle’s technology resembled the intelligent technology in ICV owing to their information technology and intelligent connected background. Thus, the study demonstrated that performance expectancy primarily influenced drivers' acceptance of automotive technology. Interestingly, a study by Madigan et al. (2016) yielded a noteworthy correlation between performance expectancy and behavioural intention. The study examined users' acceptance level of the automated road transport system. Particularly, the most essential prediction of behavioural intention observed was performance expectancy, which suggested a positive correlation. Hence, the first hypothesis (H1) was proposed:

H1: There is a relationship between performance expectancy and consumer purchase behaviour of ICVs.

Effort Expectancy and Purchase Behaviour of ICVs

Effort expectancy refers to the degree of ease associated with using the system (Venkatesh et al., 2003). Typically, effort expectancy is pivotal in the consumers' behavioural intention towards IoT in the healthcare industry (Ben Arfi et al., 2021). A study by Shin and Lee (2021) discovered that performance could significantly impact consumers' intention to use NFC mobile wallets, presenting a positive correlation. The intelligent connected features of the ICV are novel technology enabling users to attain an intelligent driving and travelling experience. This technology necessitates consumers to use this method with minimal exertion, which contains all the essential information and tools required to assist consumers in utilising this new system. Another study by Fleury et al. (2017) documented that effort expectancy was the primary factor influencing the direct and indirect determination of behavioural intention. Hence, the second hypothesis was developed:

H2: There is a relationship between effort expectancy and consumer purchase behaviour in ICVs.

Social Influence and Purchase Behaviour of ICVs

The social influence on the intention to use technology can vary depending on different periods and settings (Fleury et al., 2017). Social influence refers to other individuals or communities' impact on a user's behavioural intentions. Certain studies have presented that social influence significantly affects behaviour intention. Conversely, the significance of this influence can vary depending on the technology or product being considered. In contrast, the user's intention to utilise a specific technology or product is more prominent (Tran et al., 2019). This observation is understood as the community to which the consumer belongs in the field of ICVs. The affiliation of this group also influences their purchasing behaviour for ICVs.

Social influence on consumers' purchase intention is primarily evident during the early and middle stages of developing a technology product (rather than the stage of consumers' voluntary purchase). Moreover, social influence can directly impact purchase intention during this period (Venkatesh and Davis, 2000). This phenomenon has been observed in examining the intent to purchase EVs in Malaysia. Nonetheless, social influence is defined as the sustainable influence of society and the significant effect on individuals (such as family and friends). A study by Abbasi et al. (2021) reported that social influence positively influenced consumers' purchase intention on EV. Hence, the third hypothesis (H3) was developed:

H3: There is a relationship between social influence and consumer purchase behaviour of ICVs.

Brand Equity and Purchase Behaviour of ICVs

Brand equity is crucial as an intangible asset of an enterprise, which is also defined in various ways (Aaker, 1996). Numerous studies have revealed the significant influence of brand equity across different products and business types. A study by (Farquhar, 1989) referred to brand equity as the added value of the brand to the product. This definition emphasised that the added value could be flexible and considered from different perspectives. Subsequently, a study by Aaker (1996) defined brand equity as the assets and liabilities associated with a brand. Conversely, the study did not mention whether brand equity included the consumer base. A separate study by Liu and Jiang (2020) examined brand equity as a moderator in the luxury hotel sector. The study discovered that brand equity functioned as a mediator between brand equity, intellectual capital, and social capital. This outcome demonstrated that companies could build internal and external brand equities by leveraging various capital factors.

Another study by Park et al. (2022) acknowledged that the value of masstige consumption could affect consumer behaviour. The study highlighted a correlation between masstige brand equity and consumer purchase intention involving luxury and premium brands or products. Meanwhile, a study by Jalilvand et al. (2011) assessed the correlation between consumer buying behaviour and brand equity in the automotive sector. The study generated a link between brand equity and consumer purchase intention. Overall, these studies emphasised the importance of brand equity in consumer purchasing behaviour. Brand equity could still produce a high research value on various products and industries, particularly in new high-tech products and ICVs. Hence, the fourth hypothesis (H4) was developed:

H4: There is a relationship between brand equity and consumer purchase behaviour of ICVs.

Intelligent Connected Features and Purchase Behaviour of ICVs

A study by Ullah et al. (2021) denoted the smart connectivity feature of an EV as a system capable of interacting and establishing connections with the surroundings while connecting users and other devices over the Internet. These features could then automatically predict the user's needs. Both intelligent connected features and smart connectivity features refer to the integration of advanced technologies that enhance a vehicle's interaction with its environment, devices, and users. According to Ullah et al. (2021), smart connectivity features involves internet-based communication between cars, infrastructure, and other devices, enabling features such as mobile applications, virtual assistants, and online diagnostics. Similarly, intelligent connected features in ICVs utilize technologies like 5G and the Internet of Things (IoT) to enable real-time data exchange and automation. Both terms emphasize automation, connectivity, and user interaction, which are critical in influencing consumer purchasing behaviour. Since the official Chinese technical standard uses the term intelligent and connected vehicle for this technology, intelligent connected features are more appropriate for this study, and the two terms can be considered equivalent. Hence, Ullah et al. (2021) defined the consumer engagement have more broad range of interactions, including awareness, interest, and ongoing interaction with the product or brand before and after a purchase. However, the purchase behaviour illustrate the decision-making process and make then lead the transaction (Dutta and Hwang, 2021). Therefore, consumer purchase behaviour and consumer engagement are closely related concepts, as both involve the consumer's interaction with ICVs.

Despite limited studies on the intelligent connected features of an ICVs, certain intelligent connected features types were focused on autonomous driving feature only. Daziano et al. (2017) investigated consumers' purchase intention for intelligent connected vehicles. The study discovered that consumers were willing to pay a higher price for the autonomous driving feature provided they were aware of the advantages of technological features. Another study by Meidute-Kavaliauskiene et al. (2021) identified the autonomous driving feature as the perceived advantages to the consumers, which established a favourable correlation with the consumers' intention to use intelligent connected vehicles. Similarly, a study by Silva et al. (2021) documented that autonomous driving benefits users' risk reduction and increases driving convenience. Hence, the fifth hypothesis (H5) was developed:

H5: There is a relationship between intelligent connected features and consumer purchase behaviour of ICVs.

Theoretical Framework

The theoretical framework is proposed in the figure 1.

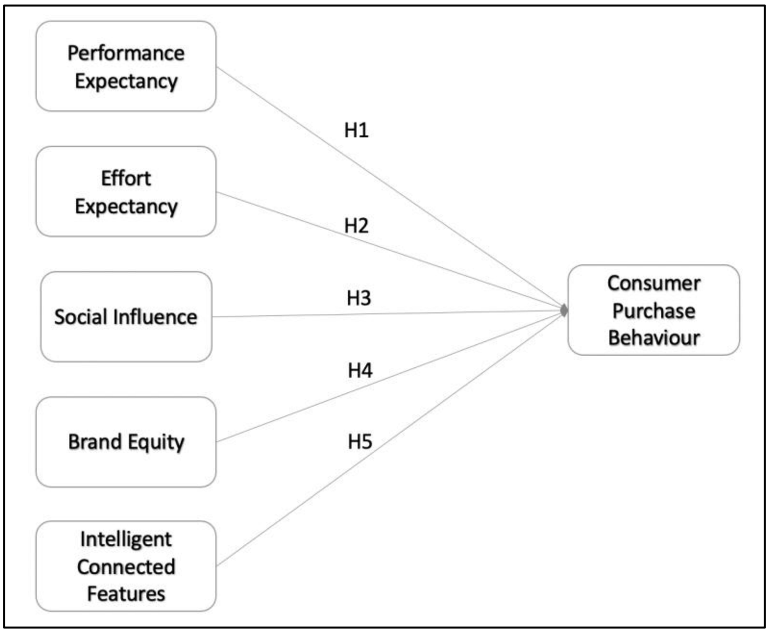

Figure 1 The theoretical framework

METHODOLOGY

This study employs a quantitative research approach to test hypotheses and analyse data, following established model and theory development frameworks (Collis and Hussey, 2019). A structured questionnaire survey was used for data collection, allowing for systematic and consistent responses from participants (Creswell and Creswell, 2018). The sample unit comprised individuals with direct relevance to the research topic, ensuring the collected data reflected a comprehensive understanding of consumer purchase behaviour in the ICV sector. In line with Hair (2015), a sampling unit represents the process through which respondents are selected based on predefined criteria to address the research questions effectively.

The traditional first-tier cities include Beijing, Shanghai, Guangzhou and Shenzhen, and the new first-tier cities include Chengdu, Hangzhou, Chongqing, Suzhou, Wuhan, Xi'an, Nanjing, Changsha, Tianjin, Zhengzhou, Dongguan, Wuxi, Ningbo, Qingdao and Hefei are considered as well, which represent the high quality economic city and large population in China. Thus, the respondents in this study where Chinese consumers live in the first-tier cities who have purchased ICVs valued at over US$28,000, in this price range typically features more comprehensive intelligent connected features.

Given that the selection of the suitable sample technique depended on the nature of the investigation, this method was employed to obtain a representative sample (Saunders et al., 2009). Five main techniques were utilised in the probability sample: simple random, systematic, stratified random, cluster, and multi-stage. Even though the research objective questions consistently influenced the probability of sample selection, several factors (sample size, sampling frame, and ease of sampling technique) could also affect the selection process (Saunders et al., 2009). The sampling frame does not have an exact list of the sampling due to the huge number of consumers. In this case, this study apply the non-probability sampling technique. Non-probability sampling (or non-random sampling) offers a range of alternative techniques to select a sample based on your subjective judgment(Saunders et al., 2009). This study involved sampling consumers residing in first-tier cities in China. Convenience sampling was used due to the unavailability of an accurate sampling list and high number of consumer groups (uncertain amount).

The inverse square root is a reliable and readily implemented conservative method. This approach employs a slightly overestimated sample size, rendering an effect significant at a given power level (Hair et al., 2021). Hence, the sample size acquired using this approach is inclined towards objectivity and suitable for the Partial least squares structural equation modelling (PLS-SEM) analysis. A study by Kock and Hadaya (2018), which applied an inverse square root method using various parameters, was used as a reference in this study. These parameters reflected a significance level of 5%, a minimum path coefficient of 0.15, and a power level of 0.8. Consequently, the minimum sample size was determined to be 275.

A questionnaire approach was employed in this study to establish the appropriate data-gathering procedure for the potential respondents (consumers residing in first-tier Chinese cities). Empirical data were collected via internet tools, specifically email and e-questionnaire. Generally, the survey questionnaire is more effective when researchers clearly define the construct and its measurement within the study scope (Sekaran, 2003). This study collected the data for approximately two months (17^{th} October 2023-16^{th} December 2023), in which 1,192 questionnaires were distributed. Consequently, 501 completed responses were received, with a response rate of 42%. The collected questionnaires were then filtered to obtain the final 302 questionnaires for this study.

This study employ PLS-SEM, which, although capable of handling small sample sizes, depends on the nature of the population for determining whether a sample is acceptable (Rigdon, 2016). A larger sample size generally yields more robust and valid results. However, it is impractical to achieve an infinite sample size in this study. PLS-SEM was chosen due to its suitability for analyzing complex models with small to medium sample sizes, like the 302 questionnaires in this study.

Measurement of Each Construct

The questionnaire used in this study was designed to collect data on consumer behaviour regarding the purchasing behaviour of intelligent connected vehicles (ICVs), with a focus on key constructs: performance expectancy, effort expectancy, social influence, intelligent connected features, brand equity and consumer purchasing behaviour. Each construct was measured using a Likert scale ranging from 1 (strongly disagree) to 7 (strongly agree), ensuring consistency in respondent feedback. The measurement item used in this study was relatively suitable for the variables selected from several literature sources. Certain measurement items were directly adopted, while others were adjusted following this study (without changing the original meaning).

The measurement table for performance expectancy, effort expectancy, social influence, and consumer purchase behaviour were adapted from studies proposed by Osswald et al. (2012), Venkatesh et al. (2012), Shin and Lee (2021), Ronaghi and Forouharfar (2020), Barata and Coelho (2021), Lin and Huang (2012), Li et al. (2020), and Wan et al. (2012). Meanwhile, the intelligent connected features measurement items of ICVs were derived from a study proposed by Ullah et al. (2021). Likewise, the brand equity measurement items were adopted from studies presented by Lavuri et al. (2022), Alamsyah et al. (2020), Paul (2019), and Jalilvand et al. (2011). Table 1 tabulates the measurement table for each study construct.

Table 1 Summary of the measurement table for each construct

Variable	Questionnaire item	Origin	Source
Performance expectancy	Using an intelligent connected vehicle could increase my driving performance.	adapt	Osswald et al. (2012)
	Intelligent connected vehicles will make my travel safer.	adapt	
	Using the intelligent connected vehicle enables me to accomplish my goals more quickly.	adapt	
	Intelligent connected vehicles will make my travel experience more comfortable.	adapt	
	I found intelligent connected vehicles helpful in my daily life.	adapt	Venkatesh et al. (2012) and Shin and Lee (2021)
	Using intelligent connected vehicles could increase my productivity.	adapt	
Effort expectancy	I anticipate that my interaction with the system will be clear and easily understandable.	adopt	Osswald et al. (2012)
	I believe I can quickly acquire proficiency in using the system.	adopt	
	I find the system easy to use.	adopt	
	Learning how to operate the system is easy for me.	adopt	
	I believe I can become a proficient user of intelligent connected vehicles.	adapt	Ronaghi and Forouharfar (2020)
	My first impression of the intelligent connected vehicle system could be clear, favourable, and comprehensible.	adapt	
Social influence	People who are important to me think that I should use intelligent connected vehicle.	adapt	Venkatesh et al. (2012) and Shin and Lee (2021)
	My passengers would feel comfortable taking the intelligent connected vehicle I am driving.	adapt	
	People whose opinions I value prefer me to use the intelligent connected vehicle.	adapt	
	My closest relatives, friends, and acquaintances are using intelligent connected vehicles.	adapt	Ronaghi and Forouharfar (2020)
	I would eagerly take the opportunity to showcase the intelligent connected vehicle to those close to me.	adapt	Osswald et al. (2012)
	Using the intelligent connected vehicle would create a positive impression on others.	adapt	Barata (2021), Venkatesh et al. (2012), and Lin and Huang (2011)
Intelligent connected features	I think the vehicle's internet connectivity function is useful.	adapt	Ullah et al. (2021)
	I think a virtual assistant for intelligently connected vehicles would be a useful feature.	adapt	
	I think it is a very convenient feature that my intelligent connected vehicle can interact with other smart devices.	adapt	
	I frequently use the mobile phone App of my car.	adapt	
	I think the intelligent connected vehicle's entertainment system is a useful feature.	adapt	
	I think the autonomous driving feature is useful.	adapt	
Brand equity	I like this brand because this brand has good quality and service support.	adapt	Lavuri et al. (2022), Alamsyah et al. (2020). Paul (2019), and Jalilvand et al. (2011)
	I like this brand because I think it is technology and intelligent-driven.	adapt	
	I consider myself to be loyal to this brand.	adapt	
	I like this brand because of brand knowledge.	adapt	
	I like this brand because it is domestic and the benchmark of my country's innovation.	adapt	
	I think choosing a top-of-mind brand in my country, state, or district is important.	adapt	
Consumer purchase behaviour	Compared to the other vehicle, I choose to purchase an intelligent connected vehicle.	adapt	Venkatesh et al. (2012)
	I like the idea of purchasing this intelligent connected vehicle.	adapt	
	Purchasing this intelligent connected vehicle is a good behaviour.	adapt	Li et al. (2020) and Wan et al. (2012)
	I think purchasing an intelligent connected vehicle is a wise choice.	adapt	

RESULT AND DISCUSSION

Reliability and Validity of the Constructs

The average variance extracted assessment of the indicator and outer loading could be applied to the convergent validity of the reflective concept (Barata and Coelho, 2021). Therefore, an outer loading exceeding 0.70 was recommended. Table 2 presents that all constructs acquire outer loading values above 0.70, suggesting that these items could remain. Considering that the average variance extracted from each reflective construct exceeded 0.5 (see Table 1), all these items were loaded onto the constructs. These items could account for over 50% of the variability in the constructs (Hair et al., 2021). Overall, each construct in this study satisfied the convergent validity and reliability criteria.

Table 2 Statistic summary of the reliability and validity of the constructs

Construct	Outer loading	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
Effort Expectancy		0.834	0.838	0.882	0.599
EE1	0.776				
EE2	0.782				
EE3	0.774				
EE4	0.759				
EE6	0.779				
Intelligent Connected Features		0.855	0.857	0.893	0.581
ICF1	0.784				
ICF2	0.792				
ICF3	0.762				
ICF4	0.764				
ICF5	0.706				
ICF6	0.762				
Purchase Behaviour		0.864	0.864	0.907	0.71
PB1	0.841				
PB2	0.829				
PB3	0.834				
PB4	0.865				
Performance Expectancy		0.882	0.883	0.91	0.629
PE1	0.793				
PE2	0.779				
PE3	0.806				
PE4	0.804				
PE5	0.788				
PE6	0.787				
Social Influence		0.877	0.881	0.907	0.62
SI1	0.784				
SI2	0.807				
SI3	0.801				
SI4	0.752				
SI5	0.761				
SI6	0.815				

An accepted guideline for assessing convergence or internal consistency in PLS was to employ a cut-off of 0.7 or higher for composite reliability (CR) scores. Thus, a CR score above 0.7 suggested that the indicator produced sufficient convergence or internal consistency (Gefen, 2000). Each Cronbach's alpha (α) value in this study was above 0.8, while each composite reliability value for the constructs was above the minimum acceptable value of 0.7. Meanwhile, each AVE value surpassed the minimal threshold of 0.5. This outcome indicated that the indicators of the constructs could explain over 50% of the variation.

Assessment for Formative Construct

The formative construct and the global measure were considered independent and dependent variables, respectively. A path coefficient exceeding the threshold of 0.7 offered significant evidence for the convergent validity of the formative construct (Hair, 2015). The redundancy analysis for the single formative construct in the framework and brand equity demonstrated a path coefficient of 0.849. This finding implied that the convergent validity of the formative construct in this study was satisfactory.

A variance inflation factor (VIF) threshold of 5 or higher indicated a potential issue with collinearity in assessing the presence of collinearity in PLS-SEM (Hair et al., 2011). Therefore, formative indicators were required to satisfy the VIF value requirement of less than five. Otherwise, the failed indicator should be excluded from the formative measurement model. Table 3 reveals that each indicator acquires a VIF value of less than 5, thus indicating the absence of multicollinearity concerns.

Table 3 Statistic summary of construct reliability and validity (formative construct)

Construct	**Original sample (O)**	**Sample mean (M)**	**Standard deviation (STDEV)**	**T statistic (|O/STDEV|)**	**P value**	**VIF**
BE1 ->BE	0.271	0.267	0.082	3.312	0.001	1.578
BE2 ->BE	0.195	0.195	0.089	2.184	0.029	1.674
BE3 ->BE	0.245	0.241	0.093	2.641	0.008	1.591
BE4 ->BE	0.253	0.249	0.087	2.887	0.004	1.474
BE6 ->BE	0.364	0.362	0.118	3.074	0.002	1.547

Assessment of Path Coefficients

Assessing the path coefficients in the structural model was a valuable approach for obtaining the answer and evaluating the hypotheses. This process could also be crucial in acquiring answers to the research hypotheses. Thus, assessing path coefficients allowed for investigating the substantial correlation between each construct in the hypothesis. Five proposed direct hypotheses between the constructs in the framework were presented in this study (see Section 3). Table 4 summarises the tests conducted on the hypotheses and their corresponding conclusions. The t- and p-values of the hypotheses were above 1.645 and less than 0.05, respectively. Consequently, all hypotheses were supported in this case. Multiple factors could also impact the consumer purchase behaviour of ICVs, including performance expectancy, effort expectancy, social influence, intelligent connected features, and brand equity.

Table 4 Summary of the path coefficients bootstrapping results

Hypothesis	**Relationship**	**Original sample (O)**	**Sample mean (M)**	**Standard deviation (STDEV)**	**T Value (|O/STDEV|)**	**P value**
H1	PE -> PB	0.163	0.16	0.045	3.649	0
H2	EE -> PB	0.183	0.182	0.045	4.067	0
H3	SI -> PB	0.178	0.176	0.052	3.429	0.001
H4	BE -> PB	0.238	0.249	0.055	4.33	0
H5	ICF -> PB	0.291	0.29	0.054	5.439	0

Assessment of the R-Square Level

A study by Cohen (1988) offered a guideline for interpreting R-square values, categorising values of 0.26, 0.13, and 0.02 as substantial, moderate, and weak, respectively. Figure 2 displays the predictive accuracy (R^2) values of purchasing behaviour in this study. The coefficient of determination for purchase behaviour was 0.644, which exceeded 0.26 and indicated a significant explanatory power. This coefficient could explain more than 64.4% of performance expectancy, effort expectancy, social influence, intelligent connected features, and brand equity. Consequently, the purchase behaviour provided an excellent explanatory power.

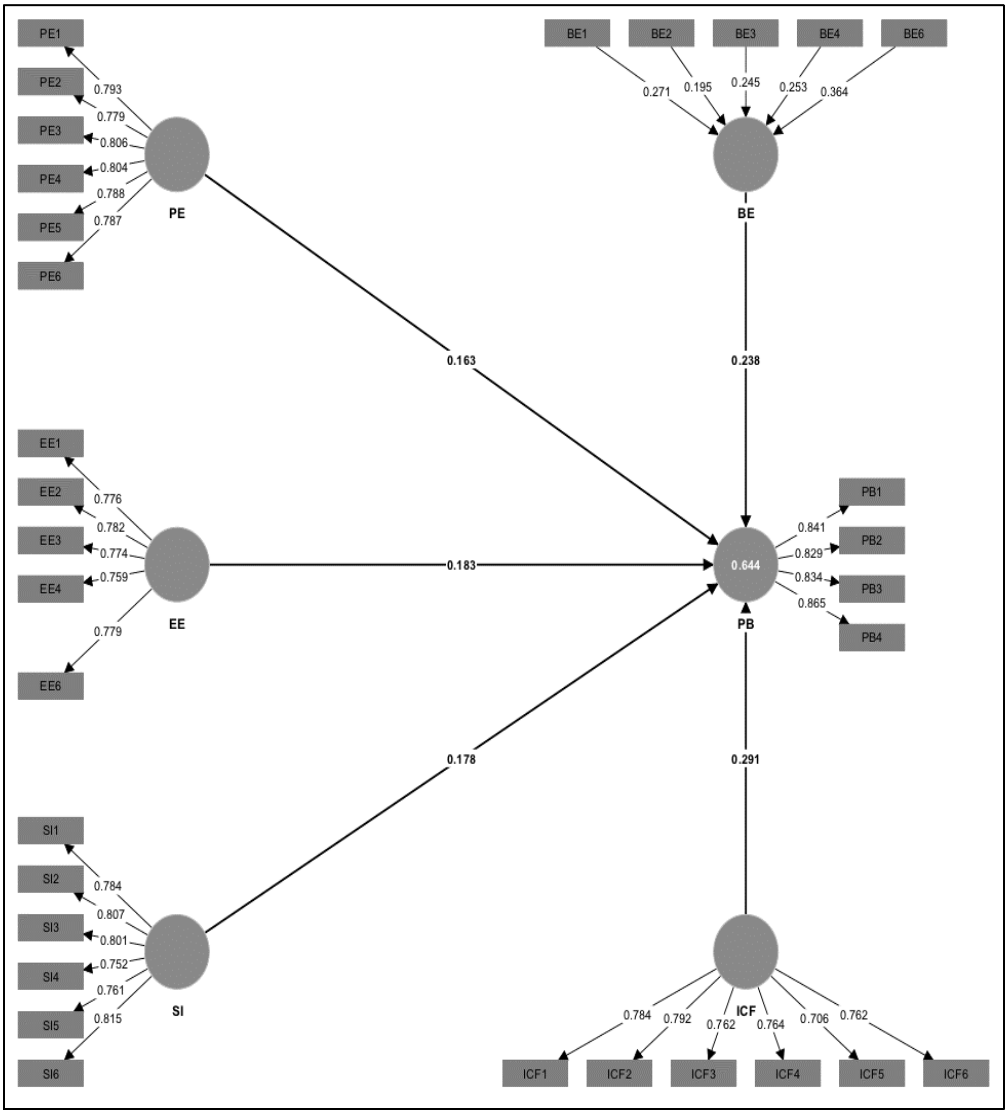

Figure 2 The PLS algorithm results of the study model

Assessment of the F-Square on $f2$

The effect size ($f2$) values of 0.02, 0.15, and 0.35 are commonly used to represent small, medium, and large effects, respectively (similar to traditional multiple regression analysis). (Chin, 2010; Cohen, 1988; Hair et al., 2016). Thus, an effect size of less than 0.02 could be considered trivial (Cohen, 1988). Table 5 reveals that the effect size of each construct is small; the f-square value is more than 0.02 but less than 0.15.

Table 5 Summary of the f-square values on effect sizes

Construct	**f-square**	**Effect size**
BE -> PB	0.089	S
EE -> PB	0.064	S
ICF -> PB	0.142	S
PE -> PB	0.051	S
SI -> PB	0.056	S

Discriminant Validity

Table 6 presents that the AVE of each reflective construct is larger than the correlation of all reflective items. This result suggested that the reflective constructs acquired sufficient discriminant validity (Fornell and Larcker, 1981).

Table 6 Summary of the discriminant validity using Fornell-Lacker

Construct	Effort expectancy	Intelligent connected features	Purchase behaviour	Performance expectancy	Social influence
Effort expectancy	0.774				
Intelligent connected features	0.447	0.762			
Purchase behaviour	0.564	0.658	0.843		
Performance expectancy	0.437	0.395	0.548	0.793	
Social influence	0.435	0.487	0.59	0.429	0.787

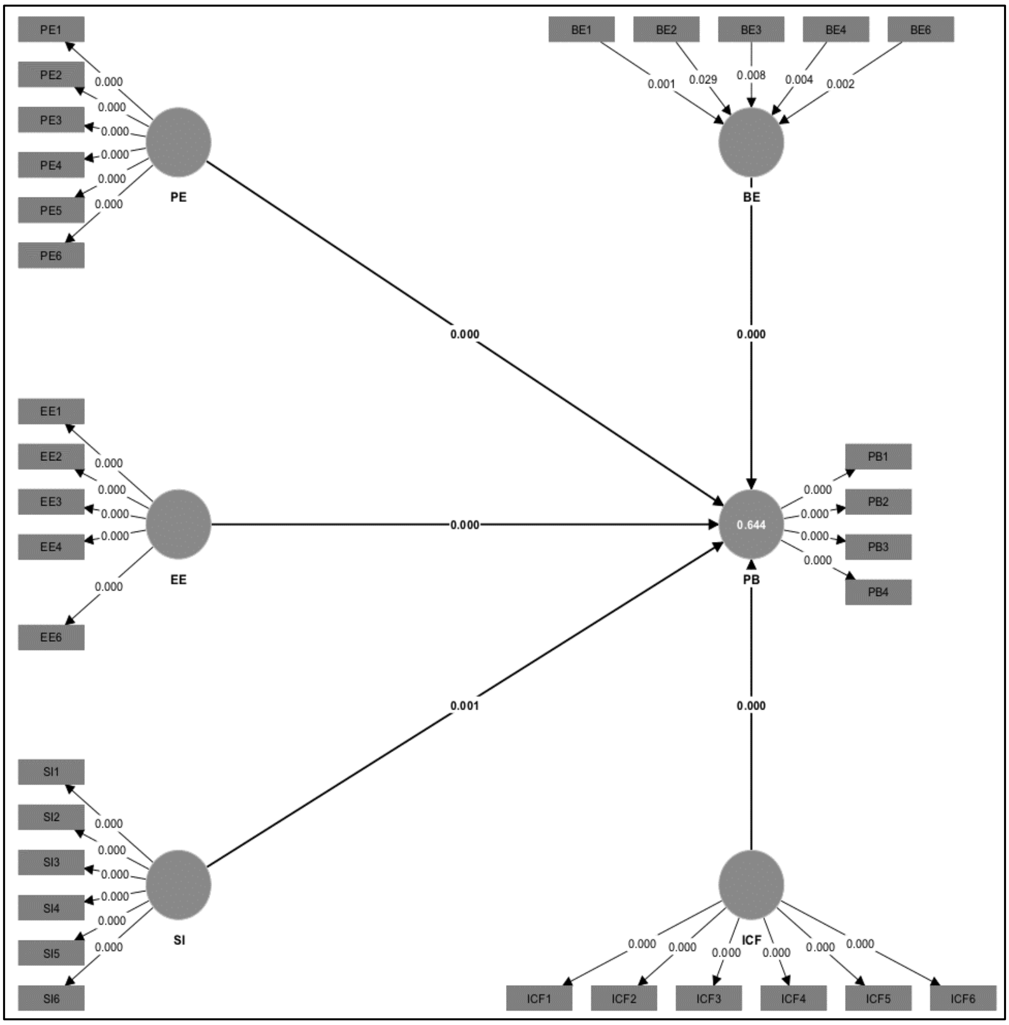

Figure 3 The bootstrapping results in this study

Practical and Theoretical Implications

This study was one of the few purchasing behaviour-based studies that addressed the limitations of previous studies regarding actual ICV purchasing behaviour. In addition, this study held significant theoretical and practical importance as a point of reference. The correlation between purchasing intention and purchasing behaviour was examined in a theoretical context, which gained a deeper understanding of consumers who purchased ICVs. Therefore, the influential purchasing factors and the consumer purchase behaviour among the purchased consumers could be accurately determined. The result of proposed hypotheses is shown in the Table 7, there are significant positive relationship between performance expectancy, effort expectancy, social influence, brand equity and intelligent connected features to the consumer purchase behaviour.

Table 7 Result of Proposed Hypotheses

Hypothesis	Description	Result
H1	There is a relationship between performance expectancy and consumer purchase behaviour.	Supported
H2	There is a relationship between effort expectancy and consumer purchase behaviour.	Supported
H3	There is a relationship between social influence and consumer purchase behaviour.	Supported
H4	There is a relationship between brand equity and consumer purchase behaviour.	Supported
H5	There is a relationship between Intelligent connected features and consumer purchase behaviour.	Supported

An empirical study was presented to verify the impact of intelligent connected features on the purchasing behaviour of ICVs. These features necessitated consideration when studying the development of ICV. Therefore, this outcome signified that advanced technological features should cater to the needs of consumers. As Chinese consumers were also interested in ICV features, the technological characteristics of ICV should not be overlooked.

This study verified the critical impact of brand equity. Manufacturers of ICV were recommended to prioritise acquiring brand assets when establishing and expanding emerging ICV brands. Even though the process could be lengthy, ICV manufacturers could develop a long-term perspective when creating their brands. This process involved building consumer awareness, fostering brand connection, cultivating brand loyalty, and enhancing perceived quality to accumulate brand equity.

Compared to Kaye et al. (2021). where French consumers showed higher acceptance of automated vehicles driven by attitudes and social influence, this study on the Chinese market reveals different consumer purchasing behaviour. In this research, key factors such as performance expectancy, effort expectancy, social influence, brand equity and intelligent connected features play a more significant role in influencing consumer purchasing behaviour of intelligent connected vehicles (ICVs). While social influence is important in both studies, Chinese consumers place greater emphasis on the intelligent connected features and brand equity, highlighting regional differences in the factors that drive consumer purchasing behaviour.

Limitations and Recommendations for Further Studies

The survey method is commonly an invaluable research technique. Despite implementing numerous bias-mitigating techniques in this study, several inherent constraints were observed. Closed-ended questions were employed in the survey, offering respondents predefined response options (including multiple-choice and scored response options). This study extended the UTAUT model by incorporating the development of ICV technology and market, enabling the application of UTAUT in analysing the purchasing behaviour of ICV. Nevertheless, the advancement of ICV technology and the prevailing market conditions developed rapidly, potentially influencing consumer purchasing behaviours alongside other purchasing factors. Thus, this study could not comprehensively elaborate on purchase factors.

Although this study examined the impact of ICV brand equity on purchasing behaviour, the correlation between brand equity and purchasing behaviour was not fully elaborated. Meanwhile, the model in this study expanded the UTAUT theory by integrating relevant influencing factors aligning with the ICV growth in the Chinese market. Further studies suggested that the research model should be continuously improved, and relevant variables should be added depending on the development status of ICV to maintain an updated status.

Several ICV brands are currently in the process of growth, and their brand equities are continuously increasing. Hence, further studies should constantly explore the role of brand equity in the market while considering the development status of brand equity in different markets. Moreover, the related policies are periodically adjusted. Further studies should also undertake comprehensive research on the role of policies on ICV purchasing behaviour based on policy adjustments. Considering the ongoing development of ICV technology, additional studies regarding the latest technological development status are necessary to conduct in-depth research on consumer purchasing behaviour.

CONCLUSION

This article provides important insights into the purchasing behaviour of China intelligent connected vehicle (ICV) consumers, revealing that performance expectations, effort expectations, social influence, intelligent connected features, and brand equity have a significant impact on consumer ICV purchasing behaviour. The findings suggest that manufacturers should prioritize the development of intelligent connected features to meet growing consumer expectations, while also focusing on building strong brand equity by increasing brand awareness, loyalty, and perceived quality. In addition, ICV manufacturers should devote more efforts to in-depth understand consumers' performance expectations, effort expectations and social impacts of ICVs, and ensure that relevant ICVs meet consumers' expectations. These practical actions will help manufacturers cater to consumer preferences and succeed in China's rapidly developing ICV industry. Meanwhile, Chinese consumer behaviour of ICVs also provide a reference for other markets where ICVs are developing rapidly.

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APPENDICES

Appendix A Demographic details of respondents

1. Gender of Respondents

Variables	Frequency (n)	Percentage (%)
Gender		
Male	184	48%
Female	167	52%
Grand Total	351	100

2. Education of Respondents

Variables	Frequency (n)	Percentage (%)
Education		
Primary School	2	1%
Middle School	38	11%
collage	99	28%
Bachelor	181	51%
Master and above	31	9%
Grand Total	351	100

3. Age of Respondents

Variables	Frequency (n)	Percentage (%)
Age		
Year 18-30	255	72%
Year 31-40	76	22%
Year 41-50	17	5%
Year 51-60	3	1%
Grand Total	351	100

4. Income Level of Respondents

Variables	Frequency (n)	Percentage (%)
Family Income		
Less than ¥100，000	85	24%
¥100，000-¥199，999	122	35%
¥200，000-¥299，999	79	22%
¥300，000-¥399，999	37	11%
¥400，000-¥499，999	10	3%
More than ¥500，000	18	5%
Grand Total	351	100