Nexus Between Artificial Intelligence, Consumer Behavior, Consumer Experience, and Purchase Intention: A Case from Shenzhen, China

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Abstract

This research aimed to investigate the influence of consumer behaviour (COB), artificial intelligence technology, and satisfying consumer experience on purchase intention (PIN). The study investigates the direct and moderating effect of hedonic motivation on the relationship between consumer behavior, artificial intelligence, satisfying consumer experience, and purchase intention for the respondents, residents in Shenzhen, China. A survey questionnaire based on past studies was finalized with a slight modification to cover the study context and key variables. Demographic factors included gender, education, and age distribution of the sample of 437 residents with experience of artificial intelligence technology, related products, and their subsequent purchase intention. The analysis showed model's substantial explanatory power with the help of R-square value of 0.842. The outer model assessment by using the Smart PLS confirmed that variables captured enough variance (average variance extracted), internal consistency reliability, and discriminant validity. The inner model assessment confirmed that artificial intelligence, consumer behaviour, and hedonic motivation directly influenced purchase intention. The interactive effect of hedonic motivation confirmed a significant presence in the relationship between artificial intelligence and purchase intention and between COB and PIN. The suggestions and limitations are well captured by the end of this research.

Keywords

Artificial Intelligence, Consumer Behaviour, Consumer Satisfying Experience, Purchase Intention, China.

1. Introduction

Artificial intelligence has proven to be a strong driving force of the fourth industrial revolution, being valued by several business organizations, governments and technology-related firms. It also has been elevated as a system of national strategic importance. High-tech organizations like IBM and Microsoft have significantly focused on artificial intelligence to achieve a competitive position in the market. These companies have pioneered several artificial intelligence-based products, which are followed by several other organizations for designing a range of products and services. Like other domains, the implications of artificial intelligence-based products and services are not only limited to education, infrastructure, tourism, health care, and like; but many countries including China have aimed to seize the opportunities offered by artificial intelligence to promote technological and domestic economic development (**Li *et al.***, 2023). China's strength in artificial intelligence field has been recognized globally, and its abilities to serve the national level strategies have now become prominent (**Li *et al.***, 2022). Meanwhile, artificial intelligence technologies have revolutionized several business aspects, including marketing, customer services and consumer interaction. However, up to which extent the level of artificial intelligence technologies is determining the consumers' purchasing intention is yet to understand and examined (**Zhao *et al.***, 2023).

Consumer behaviour has been regarded as a multifaceted area of research where studies have provided several meaningful insights and aspects like personalization, engagement and presumption (**Lim *et al.***, 2023). In the field of consumer behaviour, there is a big difference in terms of product information being perceived by different consumers. Therefore, during the consumption process, consumers tend to evaluate and make different types of purchase decisions which are primarily linked with product information. For this purpose, products can be divided into two major categories. The first is entitled as hedonic products, and the second is known as utilitarian. The utilitarian products are those types of products or services that are mainly functional or instrumental (**Bettiga *et al.***, 2020), with the core motive to solve the customer's problems and address specific tasks being assigned by customers. Examples of these products include microwaves, laptops, and shampoo. The other side of the product line encompasses the hedonic products to provide some sensory and emotional experience to customers like fantasy, pleasure and fun during usage (**Shao; Li**, 2021). Therefore, it is observed that marketing strategies vary by product type and influence of the decision-making behaviour of the consumers (**Park *et al.***, 2016). However, both types of products are based on purchase motives and efficacy.

Past studies claim that satisfaction of the consumer is linked with an affective state, rather than cognitive. Therefore, a customer-satisfying experience has been referred to as fulfilling the customer's response, which further combines the factors of emotional response and product evaluation (**Hsu *et al.***, 2015). Moreover, service satisfaction can be examined by focusing on multiple factors like interest, enjoyment, anger, sensible choice and surprise (**Wang *et al.***, 2011). Moreover, studies have also justified the relationship between consumer experience and purchase intention by taking samples from different regions and product lines. These studies chiefly focus on consumer experiences in retail for the consumer experience and repeat purchase intention (**de Kervenoael *et al.***, 2024), cross-border E-commerce (**Chen; Yang**, 2021), consumer purchase intention and affective engagement (**Bilal *et al.***, 2024), and several other domains. Therefore, the significance of the satisfying consumer experience by reflecting through purchase intention is considerable in nature (**Benoit; Belkacemi**, 2023).

The earliest definition of motivation has been given by **Babin *et al.*** (1994) who divided motivation into two major domains; hedonic and utilitarian. Hedonic motivation (**Ali *et al.***, 2022) has been referred to as the enjoyment or the level of pleasure received from the utilization of the technology. For this purpose, such motivation has a big role for the acceptance of the technology and its usage (**Brown; Venkatesh**, 2005). More specifically, hedonic motivation, under the shadow of technology acceptance model, is regarded as the perceived enjoyment being received by the consumer, where enjoyment is a type of intrinsic motivation and strongly predicting the attitude towards online purchase (**Childers *et al.***, 2001). Several perspectives of hedonic motivation have been defined in literature including the role, value, adventure, social, gratification, and finally the idea motivation. Several shopping applications are bringing the fun and enjoyment for the customers by providing several features.

Although, hedonic motivation is a good indicator to capture the customers' attention, literature has yet to explore its direct and moderating effect on the relationship between artificial intelligence technology, consumer behaviour, satisfying consumer experience and purchase intention for which this research has been carried out. The current study aimed to fill this research gap in terms of moderating effect of hedonic motivation as a variable on other constructs like artificial intelligence, consumer behaviour, and satisfying consumer experience towards purchase intention, in the context of China.

2. Literature Review

Artificial intelligence is a growing field and its correlation with consumer behaviour, and purchase intention is getting the attention of both researchers and policymakers specifically in technology and innovation industry. **Bilal *et al.*** (2024), in their empirical analysis, inferred that artificial intelligence has changed the way of online shopping. By using the social support theory, their study examined artificial intelligence, social media engagement of consumers, and consumer experience as variables on a sample of 467 respondents. The results revealed that artificial intelligence is positively connected with the consumer experience and engagement. Additionally, more satisfied consumers are connected with the consumer experience and social media engagement, leading to an amplified purchase intention. This study thus led to prove that artificial intelligence can be used to improve consumer experience.

In another study, **Chang *et al.*** (2023) and focused on travel industry and shared the view that artificial intelligence chatbots are pervasive in a similar industry as it is significantly alleviated the concerns of solo travellers regarding the booking and planning of trips. A sample of 281 solo-travellers was collected and analzyed using the multi-method approach covering the PLS-SEM and fuzzy-set qualitative comparative analysis. The PLS-SEM method results show that trendiness, communication, satisfaction, and competence are connected with the purchase intention. **Uzir *et al.*** (2023) and express that applied artificial intelligence is one of the advanced forms of technology that help remove several limitations of human beings. The utilization of the smartwatch as among the key artificial intelligence-based products have been evaluated. The results by using the empirical estimations claim that service level, quality of the device, usage experience and satisfaction level of the customers are the key factors for making positive words of mouth among family and friends.

The nexus between consumer behaviour and purchase intention reflects several points specifically for developing marketing strategies. **Prakash *et al.*** (2024) and say that the emerging cosmetics retail market has been transformed into green. However, literature pays little attention towards the green consumer purchase intention. The study addresses this gap by applying the empirical analysis using the Smart PLS-SEM. The study findings reflect that factors like eco-friendly packaging, pro-social interaction, and pro-environmental beliefs are positively connected with the consumers' purchase intention and motivation level. In cosmetic formulation, the study provides several policy suggestions for policymakers and brand mangers.

Lee and Lee (2015) also attempted to create a link between purchase intention and consumers' purchase behavior in E-commerce. Based on the theoretical foundation of the product value distribution, the study proposed that the expected product value determines the purchase intention. **Bargoni *et al.*** (2023) conducted the investigation for the purchase intention through three dimensional factors known as product and service quality, emotional appeal, and social responsibility of the corporation. An online survey was conducted and a final sample of 502 millennials was analzyed by applying the regression methodology. It was found that purchase intention was positively influenced by the family firms' characteristics. **Ghosal *et al.*** (2021), too, examined the trend in the rural consumer behaviour and purchase intention. A cluster analysis technique was applied, which further divided the consumers into different homogenous categories. The results were found to be beneficial for the farming strategy as per the market design.

The determinantal effect of the consumer experience on the purchase intention also has both theoretical and practical implications. **Esmaeilpour and Mohseni** (2019) and examine the effect of the consumer experience on the purchase intention. Using the convenient sampling technique, the study collected a sample of 385 consumers of restaurants and fast-food stores. The study findings through structural equation modeling technique generate the output that five dimensions of customer experience, including the behavioural experience, affective and cognitive experience, social and sensory experience, are positively linked with the purchase intention. Therefore, the owners and managers at the restaurants and fast-food stores need to focus on these given dimensions of customer experience for better purchase intention. **Chen and Yang** (2021) and conducted a cross-border investigation for the relationship between customer experience and purchase intention. 321 copies of online survey questionnaire were utilized by applying the structural equation modelling technique. The study results visualize the connection between customer experience and purchase intention, for which network structural embeddedness is a key mediator.

Past literature also uncovers the hedonic motivation as the major determinant of purchase intention. **Santo and Marques** (2022) and explore several determinants of online purchase intention during COVID-19. Due to such pandemic, the market for online purchases was growing rapidly. Therefore, authors investigated the determinantal effect from the hedonic motivation, access to information, trust, and price factors. A total of 750 online questionnaires were administered, whose results showed that online purchase intention was partly expressed by factors like hedonic motivation, online price perception, and trust in E-commerce websites. Besides, other studies (**Anderson *et al.***, 2014; **Sharifi Fard *et al.***, 2019) have also investigated different motivation types (hedonic and utilitarian) on purchase intention, yet the gap is still existing specifically in terms of the moderating effect of the hedonic motivation on the relationship between artificial intelligence, consumer behaviour, and satisfying consumer experience towards purchase intention for the Chinese residents. This research has reasonably filled this gap and found that there is a significant and positive impact of artificial intelligence, consumer behaviour, and hedonic motivation on purchase intention. The interactive effect of hedonic motivation confirms a significant presence on the relationship between artificial intelligence and purchase intention and between consumer behaviour and purchase intention. Figure 1 justifies the research framework as tested.

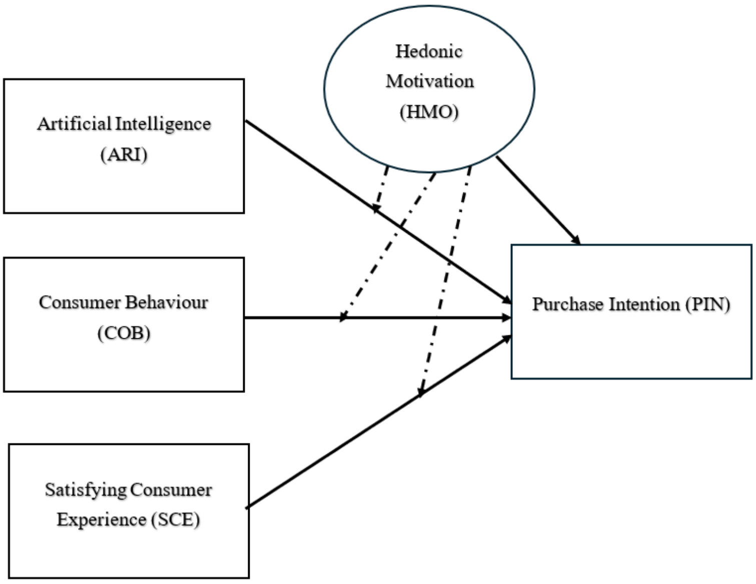

Figure 1: Research Framework.

3. Methodology

A questionnaire comprising items validated in previous studies was designed for this study, with a few modifications, to align with the constructs of the study. Table 1 reflects the description of the variables, whereas Appendix 1 covers the questionnaire used in this study.

Table 1: Questionnaire Items and their Sources.

Variable	Items/measures	Source
Consumer Behavior (COB)	1. Using the product helps me complete the task faster. 2. Using the product will improve my results. 3. Using the product will enhance my efficiency. 4. Using the product will make the task easier.	(**Ventre; Kolbe**, 2020)
Artificial Intelligence (ARI)	1. AI enhances audience, image, and sentiment analysis. 2. AR and VR are utilized for marketing and user engagement. 3. Audience analysis is key to effective marketing strategies. 4. AI uses customer-related data like purchases and demographics. 5. AI tools for brand logo recognition help analyze user interests. 6. Automatic image annotation benefits user expectations and improves user experiences.	(**Nazir *et al.***, 2023)
Satisfying Consumer Experience (SCE)	1. Social media proliferation has influenced consumer needs for interactive, collaborative, and personalized interactions. 2. Social media use reflects consumers' hedonic behavior. 3. Social media use reflects consumers' pragmatic behavior. 4. Social media use reflects consumers' sociability behavior. 5. Social media use reflects consumers' usability behavior.	(**Nambisan; Watt**, 2011)
Purchase Intention (PIN)	1. I am interested in purchasing the AI-based product. 2. I may consider buying AI-based in the future. 3. I would recommend AI-based product to others.	(**Vuong; Khanh Giao**, 2020)
Hedonic Motivation (HMO)	1. Using mobile shopping apps is enjoyable. 2. Using mobile shopping apps is fun. 3. Using mobile shopping apps is highly entertaining.	(**Chopdar *et al.***, 2018)

The questionnaire was distributed to a sample comprising educated professionals in the Chinese businesses and organizations residing in Shenzhen, China. These respondents significantly differed in age, gender, and educational backgrounds, therefore highlighting the city's fast growth and strong technological influence. All respondents were professionals, comfortable with new technologies, and working across various technological fields. Moreover, they also used several technological products covering the dimensions of artificial intelligence. Their feedback gave important insights into consumer habits in an urban setting where technology plays a big role. This sample from Shenzhen helped understand consumer views in one of China's most vibrant cities regarding the purchase intention, artificial intelligence technologies, customers' satisfying experience, and hedonic motivation. The data was analyzed by applying various descriptive and quantitative techniques. Figure 2 presents the steps utilized in this study.

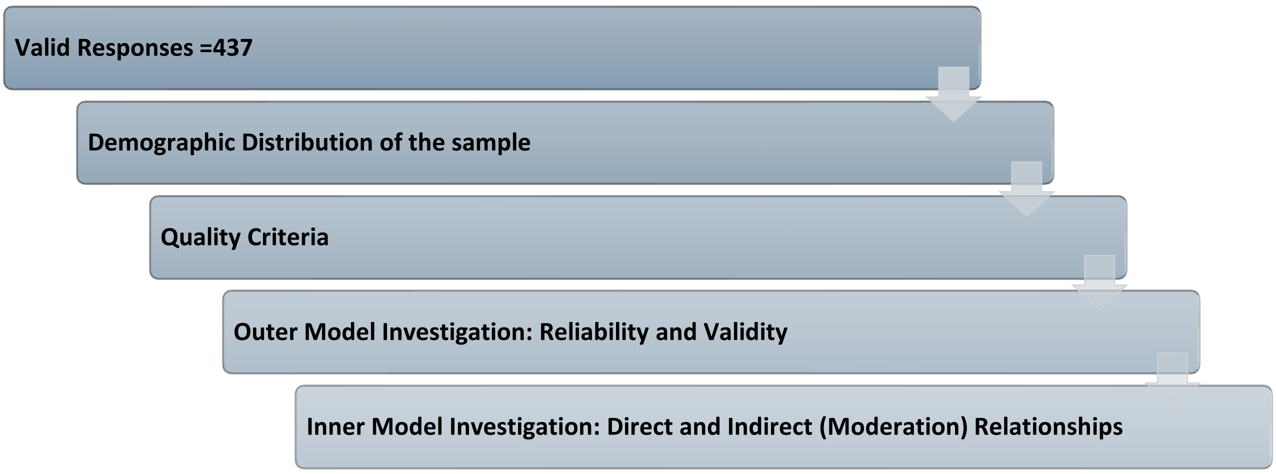

Figure 2: Methodological Sequence.

4. Results and Discussion

4.1. Demographics

Detailed demographic information is shown in Table 2, reflecting gender, age, and educational background of respondents. Overall, 48% female and 51% male respondents participated in this study, covering the age distribution from 18 years to over 46 years. However, most of the participation was observed from the respondents aged 26-35 years, covering 36% of the total sample of 437 respondents. The educational background revealed that 45 respondents had studied in specialized schools, whereas 290 had completed their college degree, followed by 102 having postgraduate studies. The demographic profile of the respondents is presented in Table 2 and Figure 3.

Table 2: Demographic Profile.

Demographic Group	Frequency	Percentage (%)
Gender		
Male	224	51.26
Female	213	48.74
Total	437	100
Age (years)		
18-25	134	30.66
26-35	160	36.61
36-45	120	27.46
46 and above	23	5.26
Total	437	100
Education		
Specialized schools	45	10.3
College degree	290	66.36
Postgraduate studies	102	23.34
Total	437	100

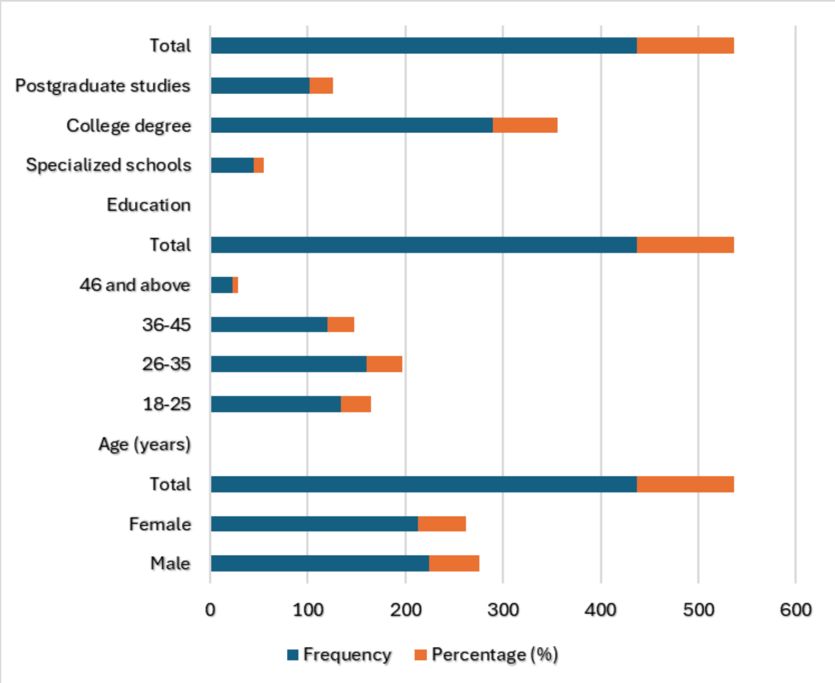

Figure 3: Demographics bar Charts for Relative Frequency and Percentage.

4.2. Quality Criteria

The quality criteria by using the Smart PLS analysis initially comes up with the R-square of the model for which purchase intention (PIN) is a main outcome variable. The R-square is a key indicator to judge for the explained variation based on all the other variables into the similar model. The existing literature confirms three major ranges of R2, where the values like 0.75, 0.50 and 0.25 are accepted as substantial, moderate, and weak levels of explanatory power (**Hair *et al.***, 2019). The results of Table 3 show that R-square for PIN is 0.842. As this value is above 0.75, it is regarded as a substantial change in the PIN, as determined by the above-explained independent and moderating variable of the same model. However, it is important to note that R2 of above 0.90 is an indication of overfit (**Hair *et al.***, 2019).

Table 3: R-square.

DV	R-square	R-square adjusted
PIN	0.842	0.838

The consideration of the internal consistency reliability was measured using different quantitative techniques. Table 4 presents Cronbach's alpha, Composite reliability (rho_a), Composite reliability (rho_c), Average variance extracted (AVE). The results cover both the lower bound and upper bound for internal consistency reliability. This is linked with the alpha values covering the lower bound and composite reliability as upper bound. The acceptable range for the Cronbach alpha is above 0.70 (**Spiliotopoulou**, 2009; **Adeniran**, 2019). For the variables ARI, COB, HMO, PIN and SCE, alpha values are 0.830, 0.832, 0.717, 0.769, and 0.868. For composite reliability, the scores of all variables are 0.834, 0.863, 0.785, 0.805, and 0.873. However, in terms of rho_a and for rho_c, findings are 0.880, 0.888, 0.872, 0.895, 0.905. Given the above-stated criteria, none of the variables was linked to poor internal consistency reliability. Table 4 also depicts the convergent validity by using the criteria of average variance extracted. The cut-off level for the average variance extracted is that its value for the given variable should be equal to or above 0.50 to finalize the presence of convergent validity (**Ahmad *et al.***, 2016; **dos Santos; Cirillo**, 2023). The output for alpha values and average variance extracted by using the Smart PLS are also shown in Figure 4 and Figure 5.

Table 4: Measurement Model Investigation.

Variables	ARI	COB	HMO	PIN	SCE
Cronbach's alpha	0.830	0.832	0.717	0.769	0.868
Composite reliability (rho_a)	0.834	0.863	0.785	0.805	0.873
Composite reliability (rho_c)	0.880	0.888	0.872	0.895	0.905
Average variance extracted (AVE)	0.594	0.665	0.774	0.810	0.655
Note: ARI- artificial intelligence, COB- consumer behaviour, HMO- hedonic motivation, PIN- purchase intention, SCE- satisfying consumer experience.					

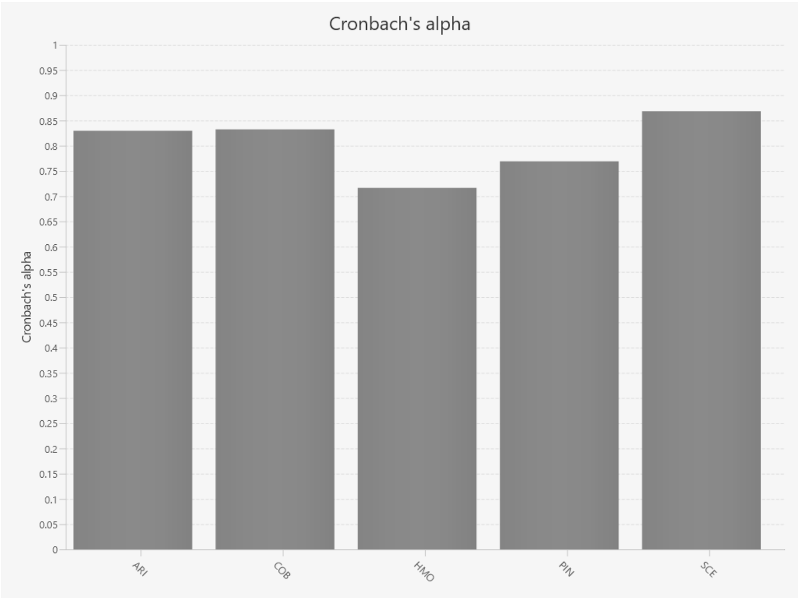

Figure 4: Alpha bar-charts of Variables.

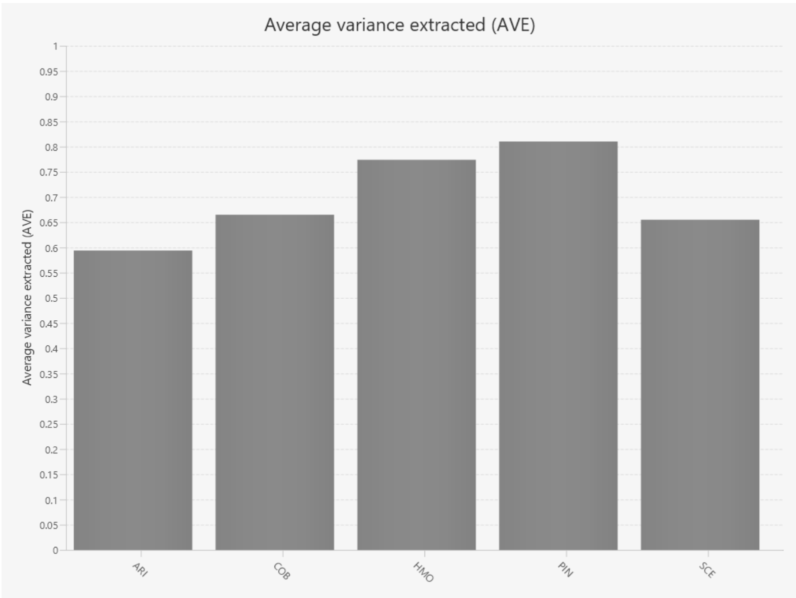

Figure 5: AVE bar-charts of Variables.

The other assessment of the formative measurement model covers the investigation of the variance inflation factor (VIF) of the selected items as seen in Table 5. The possible concerns related to the presence of the collinearity between the latent variables exist when the VIF scores are above 5 (**Kyriazos; Poga**, 2023; **Feng; Chen**, 2024; **Streukens; Leroi-Werelds**, 2023). The VIF for the items ARI1 (1.789), ARI2 (1.948), ARI3 (1.791), ARI4 (2.345), ARI5 (2.139), COB1 (1.555), COB2 (1.912), COB3 (2.160), COB4 (1.848), HMO2 (1.453), HMO3 (1.453), PIN1 (1.641), PIN2 (1.641), SCE1 (1.732), SCE2 (1.964), SCE3 (2.464), SCE4 (2.507), SCE5 (2.360). The VIF for all these items is reasonably less than 5, confirming that these items are free from collinearity bias.

Table 5: Variance Inflation Factor for the Selected Items.

Items	VIF
ARI1	1.789
ARI2	1.948
ARI3	1.791
ARI4	2.345
ARI5	2.139
COB1	1.555
COB2	1.912
COB3	2.160
COB4	1.848
HMO2	1.453
HMO3	1.453
PIN1	1.641
PIN2	1.641
SCE1	1.732
SCE2	1.964
SCE3	2.464
SCE4	2.507
SCE5	2.360
Note: ARI- artificial intelligence, COB- consumer behaviour, HMO- hedonic motivation, PIN- purchase intention, SCE- satisfying consumer experience.	

The HTMT ratios of the variables are shown in Table 6. This ratio is used to evaluate the discriminant validity between different measurement constructs. Ideally, the ratio between two latent variables should be less than 0.85 to confirm that discriminant validity significantly exists. However, it is important to note that for ideally and conceptually similar constructs, HTMT should be less than 0.90 (**Ringle *et al.***, 2023; **Guenther *et al.***, 2023). The presented findings truly capture the argument that the HTMT ratio of ARI, COB, HMO, PIN and SCE with the other variables is less than 0.85, as seen in Table 5. Therefore, the discriminant validity is not challenged by any means.

Table 6: HTMT Ratio of Variables.

	ARI	COB	HMO	PIN	SCE
ARI					
COB	0.425				
HMO	0.395	0.813			
PIN	0.400	0.815	0.517		
SCE	0.584	0.432	0.713	0.626	
Note: ARI- artificial intelligence, COB- consumer behaviour, HMO- hedonic motivation, PIN- purchase intention, SCE- satisfying consumer experience					

Due to lower factor loadings, few items were removed to improve the fitness of the model. The removed items were ARI6, PIN3, and HMO1. After removing these items, the measurement model test was again run through Smart PLS. The output is presented in Table 7 using the discriminant validity criteria and, more specifically, the loadings and cross-loadings.

Table 7: Loadings and Cross-Loadings.

	ARI	COB	HMO	PIN	SCE
ARI1	**0.738**	-0.374	0.262	0.250	0.483
ARI2	**0.798**	-0.271	0.282	0.289	0.395
ARI3	**0.765**	-0.226	0.234	0.255	0.400
ARI4	**0.771**	-0.232	0.182	0.210	0.292
ARI5	**0.780**	-0.266	0.252	0.246	0.352
COB1	-0.264	**0.725**	-0.533	-0.389	-0.278
COB2	-0.333	**0.853**	-0.628	-0.625	-0.335
COB3	-0.298	**0.875**	-0.480	-0.635	-0.300
COB4	-0.263	**0.800**	-0.432	-0.473	-0.304
HMO2	0.220	-0.478	**0.833**	0.637	0.498
HMO3	0.325	-0.620	**0.924**	0.123	0.504
PIN1	0.330	-0.603	0.324	**0.926**	0.505
PIN2	0.252	-0.604	0.488	**0.873**	0.428
SCE1	0.440	-0.365	0.471	0.466	**0.779**
SCE2	0.357	-0.329	0.417	0.394	**0.781**
SCE3	0.406	-0.282	0.444	0.392	**0.840**
SCE4	0.401	-0.199	0.415	0.366	**0.813**
SCE5	0.420	-0.310	0.521	0.471	**0.832**
Note: ARI- artificial intelligence, COB- consumer behaviour, HMO- hedonic motivation, PIN- purchase intention, SCE- satisfying consumer experience					

The loadings for the items named ARI1 (0.738), ARI2 (0.798), ARI3 (0.765), ARI4 (0.771), ARI5 (0.780) were found as above 0.70 and cross-loadings were also less than these loadings. The COB items viz., COB1, COB2, COB3, and COB4 had their loading values as 0.725, 0.853, 0.875, and 0.800, which are also above 0.70. The HMO items, HMO2 and HMO3, shows loadings of 0.833 and 0.924. For PIN items, PIN1 and PIN2, loading scores are 0.926 and 0.873. For SCE items, SCE1, SCE2, SCE3, SCE4, and SCE5, loadings are shown as 0.779, 0.781, 0.840, 0.813, and 0.832. The cross loadings for all these items are less than these loadings, so, it was confirmed that discriminant validity was presented well.

4.3. Testing the Direct Effect

4.3.1. Impact of ARI on PIN

The testing of the direct effect between variables are presented in Table 8, comprising all the possible direct paths. In the first path, the impact of ARI on PIN was investigated. The path coefficient, T-statistics and P-value for this path are 0.125, 6.137, and 0.0000 respectively. This positive effect leads to the inference that keeping the rest of the factors as constant, one percent upsurge in ARI would result in an increase of 0.125% in the purchase intention of the consumers in China. This coefficient was accepted as significant due to lowest p-value as 0.000 which falls in the criteria of 1% chance of error. Given this chance of error, it was assumed that ARI is a significant factor that positively changes the consumers' purchase intention in China.

Table 8. Testing the Direct Effect

Path Analysis	Original sample (O)	T statistics (O/STDEV)	P values
ARI -> PIN	0.125	6.137	0.000
COB -> PIN	0.148	3.401	0.001
SCE -> PIN	-0.003	0.084	0.933
HMO -> PIN	0.810	20.528	0.000
Note: ARI- artificial intelligence, COB- consumer behaviour, HMO- hedonic motivation, PIN- purchase intention, SCE- satisfying consumer experience			

Given these direct effects of ARI on PIN, it can be interpreted that although artificial intelligence tools aim to analyze the interactions and sentiments of users on different social media platforms, such tools also provide the brands with valuable insights regarding the customers' preferences. Therefore, by properly understanding the audiences' sentiments, companies can customize and design their marketing messages to more strongly align with their consumers, while increasing the chances of boosting sales. Additionally, augmented reality and virtual reality also create some engaging experiences for the customers that allow users to interact with products in some exciting manner. These engagements include virtually trying on items before making a purchase decision. This boosts customers' confidence and fosters a deeper connection towards the products offered by the companies, hence leading to a greater intention to buy that specific product or set of products. The other factual discussion encompasses that effective audience analysis enables the brands to segment their target markets accurately, allowing the companies to develop personalized marketing strategies that stand on loyalty and trust.

There are a few additional benefits of using AI-based technology for promoting purchase intention, based on the analysis of customer data, which can facilitate checking for past purchases and demographics, allowing the brands to predict the future buying behavior of the customers. Additionally, brand logo recognition with the help of artificial intelligence, can insist on understanding the users' interests and engagement levels. Consumers are more likely to make purchase decisions when they frequently see their favourite brands in their feeds. Hence, this suggests a direct connection exists between AI technology and customers' purchase intention, and the first direct path between ARI and PIN was accepted at 1% significance level.

4.3.2. Impact of COB on PIN

The path between COB and purchase intention is well presented using the sample coefficient, t-statistics and p-value (see Table 8). The sample coefficient is 0.148%, showing a directional result, causing a productive change in the purchase intention determined by the COB. This effect is accepted because of the significant results and t-statistics as 3.401. This means there is a significant and positive change in the PIN when accounting for the COB of the Chinese respondents. A positive change in consumer behaviour means a leading change in purchase intention. Several points are linked on the relationship between consumer behaviour and purchase intension. For example, consumer behavior is all about understanding how individuals make their choices based on their relative needs, preferences, and past experiences. More specifically, when brands focus on these aspects, they can adjust their products and services to better fit what the consumers are looking for. Ultimately, it boosts the chances that people will decide to buy a specific product or service.

Additionally, the concept of smart marketing strategies and tactical planning which are based on COB can significantly influence purchase intentions. For example, targeted ads, special promotions, and recommendations can make the offers more attractive while motivating the consumers to consider purchasing. Therefore, the positive relationship between purchase intention and COB is quite natural. The existing literature also provides evidence to justify this relationship. For example, **Lee and Lee** (2015) examine the relationship between purchase intention and consumer behaviour. The study findings show that expected product value is significant only when repeated purchase is assumed. Likewise, **Dangi *et al.*** (2020) aim to determine the connection between consumer buying behaviour and purchase intention of the organic food. Having analyzed 19 studies and 154072 consumers from 2001 to 2020, the study's results confirmed that the consumers' psychographic, demographic and product-relevant factors are more pronounced than the related supply-chain factors. Besides, a few other studies also confirmed the logical connection between COB and purchase intention through a diversified sample and empirical estimations (**Bargoni *et al.***, 2023; **Ali *et al.***, 2023; **Srivastava *et al.***, 2023).

4.3.3. Impact of SCE on PIN

The path analysis, specifically the direct relationship between SCE and PIN, yielded some insignificant statistical results. This was confirmed by focusing on the t-value of 0.084 and p-value which is above 5% level of significance. As the relationship is insignificantly negative, it is inferred that no relationship exists between SCE and PIN in the context of the present study.

4.3.4. Impact of HMO on PIN

The last path analysis of the direct relationship covers the HMO and PIN. The coefficient is 0.810 with the highest t-value of 20.528, compared to the other relationships explored earlier (See Table 8). This states that HMO promotes purchase intention by 0.810% while considering the other factors as constant. The given result of 0.810 indicates that HMO is a productive factor for boosting the purchase intention in the similar direction. The concept of HMO means those set of activities that bring pleasure or enjoyment and satisfaction among the consumers which mainly comes from the utilization of the technology which further determines the level of technology acceptance (**Chopdar *et al.***, 2018). HMO is closely related to the intention to buy because people are naturally associated to the things that bring for them the factors like joy, pleasure, excitement, or happiness. When a product seems like it will provide a good experience over some time along with the emotional satisfaction, people tend to feel a stronger motivation to buy that specific product.

As a result, such type of connection determines the positive linkage between HMO and purchase intention, by the end. The current literature, in recent times, supports the relationship between HMO and PIN. For example, **Anderson *et al.*** (2014) claim that social networking is a good option to connect family and community. For this reason, the role of the consumer's motivation by using the social media is a good marketing strategy for the retailers. The study examined the role of hedonic and utilitarian motivation in determining the purchase intention level towards the retail Facebook pages. The results reflect that loyalty is positively connected with the purchase intention. **Sharifi Fard *et al.*** (2019) also reiterated to examine the direct relationship between HMO and purchase intention, and emphasized on a moderating relationship between HMO and PIN. Their study results confirmed that both hedonic and utilitarian motivations are positively connected with the purchase intention of 370 undergraduates and graduates from four different universities in Malaysian region. Therefore, this research also confirms the similar productive relationship between HMO and PIN, but for the sample of the Chinese region.

4.4. Testing the Moderation

4.4.1. Moderating Effect of HMO between ARI and PIN

Table 9 presents how HMO is a significant or insignificant moderator of the relationship between PIN and the rest of the independent variables. The first path deals with the moderating effect of the HMO between ARI and PIN. The path coefficient is 0.150 and t-value is 3.221, leading to a p-value as 0.001, significant at 1%. The overall results confirm that there is a significant moderating effect from hedonic motivation on the relationship between ARI and PIN. This moderating effect is also reflected by the graphical presentation when accounting for low and high HMO, as shown in Figure 6. It shows that the interaction term significantly moderates the relationship between ARI and PIN. More specifically, it shows that the effect of ARI on PIN is stronger when the HMO is high compared to when the HMO is low.

4.4.2. Moderating Effect of HMO between COB and PIN

In Table 9, the second path of the moderating effect of HMO covers the relationship between COB and PIN. The path shows the coefficient as 0.797, with the highest t-score of 18.371. This path is significant at 1%, confirming that the interaction term of HBO and COB positively and significantly leads to a higher purchase intention among the same respondents (See Figure 6). These results show that COB is also positively connected with the PIN. However, whether this moderating effect strengthens the relationship between COB and PIN, an interaction term graph was generated using the tool package through MS Excel. The interaction graph (Figure 7) shows that HBO positively strengthens the relationship between COB and PIN. The graph further recommends the interaction effect using high and low HMO among the respondents. It states that the effect of COB on PIN is stronger when the HMO is higher, compared to the situation where the HMO is low among the same respondents. Therefore, the study recommends the significant interaction effect of HMO between COB-PIN relationships in China.

Table 9: Testing the Moderating Effect.

Path Analysis	Original Sample (O)	T Statistics	P values
HMO x ARI -> PIN	0.150	3.221	0.001
HMO x COB -> PIN	0.797	18.371	0.000
HMO x SCE -> PIN	0.005	0.158	0.875
Note: ARI- artificial intelligence, COB- consumer behaviour, HMO- hedonic motivation, PIN- purchase intention, SCE- satisfying consumer experience			

Besides, the results did not support the moderating effect of the HMO between SCE and PIN as the p-value is 0.875 which is above 5% level of significance.

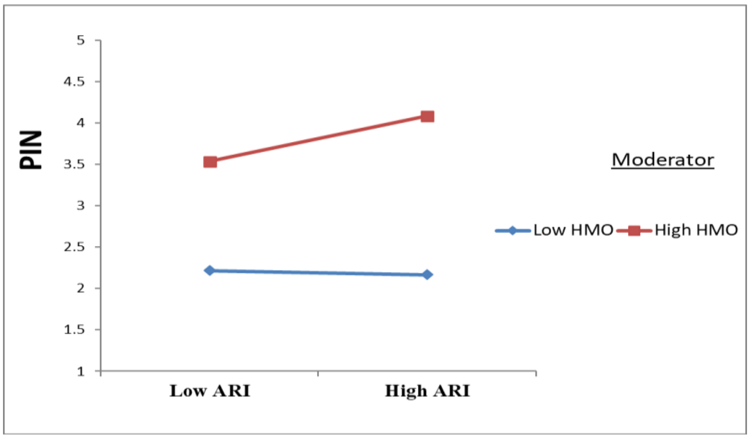

Figure 6: Moderating effect of HMO between ARI and PIN.

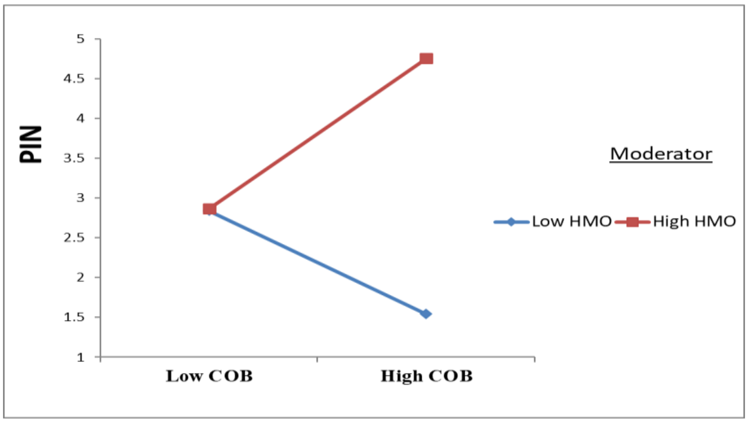

Figure 7: Moderating effect of HMO between ARI and PIN.

5. Conclusion and Policy Recommendations

This study has substantially explored the causal effect of artificial intelligence, consumer behaviour and satisfying consumer experience toward Chinese residents' purchase intention. The study further explored the associated mechanism on the relationship between ARI, COB, SCE, and PIN among the same respondents using a detailed discussion while providing a support from the past empirical studies. The study also explored how the hedonic motivation moderated the linkage between ARI, COB, SCE and PIN. The study used advanced data analysis techniques including inner and outer model assessment using the Smart PLS, and structural equation modeling method. The results verify that artificial intelligence, consumer behaviour, and the direct effect of the hedonic motivation are key factors of leading the purchase intention for a sample of 437 respondents, of different age groups and educational background and comprising both genders. The additional statistical analysis covered the moderating effect of the hedonic motivation. The moderating effect favored the relationship between ARI and PIN and between COB and PIN for which hedonic motivation significantly moderated and strengthened their relationships, provided that the condition of higher level of hedonic motivation would be considered.

This study is among the initial contributions in the field of artificial intelligence products and their subsequent relationship with the purchase intention. The rapid technological advancement in the Chinese region signifies the positive connection between artificial intelligence and purchase intention. Aiming such correlation and based on the findings of the study, a few policy recommendations can be given. First, the study suggests that related authorities and companies involved in developing ARI-based products need to focus on ethical regulations like user privacy, data transparency and fairness to foster consumer trust towards artificial intelligence-related products. The study also recommends supporting the ARI startups by financial aids, tax incentives for investors, and standardization of ARI-based user experience. Second, the study recommends to conduct educational and awareness campaigns that foster consumer trust in similar products. Moreover, the facilitation for the adoption of ARI-based products can also create an environment of higher purchase intention among the Chinese respondents, specifically, and for the rest of the region, on general grounds. Thirdly, based on the direct and moderating effect of the hedonic motivation, this research suggests that companies involve in developing ARI-based products and services need to encourage the customer experience by using the experiential marketing strategies. Moreover, a strong public-private collaboration for hedonic product innovation which can boost the customers' fun, happiness, and satisfaction, is also recommended for different policymakers, including those working in the technology industry.

The study faced several limitations that need to be considered in future research. For example, this study was limited to targeted age groups, and confined to regional and cultural discrepancies. Hence, the results may not be fully applicable for other economies. Secondly, the study considered only the quantitative method of data collection and analysis, and did not pay attention to qualitative methods like interviews which, in several circumstances, has been observed as a much better technique for exploring consumer behaviour, purchase intention, and level of hedonic motivation. Future studies may go for qualitative or mixed method research designs.

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Appendix-1

Questionnaire on Consumer Behavior, Technology Use, and Purchase Intention

Section 1: Demographics

1. Please provide your information by selecting the most appropriate options.

Gender
- ☐ Male
- ☐ Female

Age (years)
- ☐ 18-25
- ☐ 26-35
- ☐ 36-45
- ☐ 46 and above

Education
- ☐ Specialized school
- ☐ College degree
- ☐ Postgraduate studies

2. Please read each statement carefully and indicate your level of agreement on a scale of 1 to 5, where: 1 = Strongly Disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, 5 = Strongly Agree.

Section 2: Consumer Behavior

1. Using the AI based product helps me complete tasks faster.

   - ☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5

2. Using the AI based product improves my results.

   - ☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5

3. Using the AI based product enhances my efficiency.

   - ☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5

4. Using the product makes the tasks easier.

   - ☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5

Section 3: Artificial Intelligence Technology

1. AI enhances audience, image, and sentiment analysis.

   - ☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5

2. AR and VR are utilized for marketing and user engagement.

   - ☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5

3. Audience analysis is key to effective marketing strategies.

   - ☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5

4. AI uses customer-related data, such as purchases and demographics, to improve services.

   - ☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5

5. AI tools for brand logo recognition help analyze user interests.

   - ☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5

6. Automatic image annotation benefits user expectations and improves user experiences.

- ☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5

Section 4: Satisfying Consumer Experience through Social Media

1. Social media proliferation has influenced consumer needs for interactive, collaborative, and personalized interactions.
 - ☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5

2. Social media use reflects my hedonic behavior (seeking enjoyment).

 - ☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5

3. Social media use reflects my pragmatic behavior (seeking practical benefits).

 - ☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5

4. Social media use reflects my sociability behavior (seeking social connections).

 - ☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5

5. Social media use reflects my usability behavior (seeking ease of use).

 - ☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5

Section 5: Purchase Intention

1. I am interested in purchasing the AI-based product.

 - ☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5

2. I may consider buying an AI-based product in the future.

 - ☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5

3. I would recommend the AI-based product to others.

 - ☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5

Section 6: Hedonic Motivation

1. Using mobile shopping apps is enjoyable.

 - ☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5

2. Using mobile shopping apps is fun.

 - ☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5

3. Using mobile shopping apps is highly entertaining.

 - ☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5

Response Rate

Details	Frequency	% share
Overall questionnaires distributed	534	100
Questionnaire returned by the respondents	464	86.891
Questionnaire with missing responses	27	5.056
Final and valid sample for analysis	437	81.835