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IMPACT OF ARTIFICIAL INTELLIGENCE (AI) TECHNOLOGIES ON PURCHASE INTENTIONS: EVIDENCE FROM E-COMMERCE AND OMNICHANNEL RETAILING IN CHINA

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IMPACT OF ARTIFICIAL INTELLIGENCE (AI) TECHNOLOGIES ON PURCHASE INTENTIONS: EVIDENCE FROM E-COMMERCE AND OMNICHANNEL RETAILING IN CHINA

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ABSTRACT

This research focuses on the impact of AI on consumers' purchase intentions within the context of e-commerce and omnichannel retailing in China. The study examines how AI technologies influence consumers' purchase intentions in e-commerce and omnichannel retailing in China. By examining these factors and considering moderating effects such as trust, perceived usefulness, and perceived ease of use, the study aims to provide insightful discoveries to businesses operating in the Chinese market and contribute to the global knowledge base. A quantitative survey was conducted to test the hypotheses involving 563 Chinese e-commerce consumers who completed an online questionnaire. Descriptive and inferential statistics were used to analyze and test the hypotheses. The results indicated significant impacts on usefulness, informativeness, irritation, and purchase intention, with p-values below the significance threshold ($p < 0.05$), specifically <0.001 for the key variables. A case study involving 30 Chinese consumers with relevant experience was conducted to complement these findings, providing additional validation and triangulation of the results. This research aims to address the research gap by investigating how AI technologies influence consumers' purchase intentions in the Chinese e-commerce market and omnichannel retailing. The findings will benefit businesses, contribute to global knowledge, and encourage further research.

Key words: Artificial Intelligence; online marketing; online shopping; e-commerce;

1 INTRODUCTION

Artificial Intelligence (AI) technology has been rapidly advancing in recent years, and its impact on various industries has been significant (Huang et al., 2019). A notable case of this advancement can be seen in the retail industry, where AI technology has been increasingly adopted in e-commerce and omnichannel retailing (Bhagat et al., 2022). AI technology has the potential to transform the retail industry by providing personalized experiences, improving operational efficiency, and increasing sales (Heins, 2022). However, its impact on consumer behavior is not well understood.

The increased use of technology has triggered the development of intelligent systems that are useful in managing and monitoring business models without involving humans in most cases (Furman & Seamans, 2019). The current economy in China and across the globe requires AI systems that can meet consumer demands in the different sectors of the Chinese economy. The system monitors the business climate by identifying customer needs and initiating functional solutions with minimal human intervention to help drive e-commerce purchase intent. Thus, AI establishes changes that allow consumers and retailers to benefit from e-commerce and omnichannel retailing.

The concept of 'a machine that thinks' stretches back to ancient Greece. AI, as we know it today, stems from the introduction of the electronic computer, and its advancement has been marked by some key milestones. In 1950, Alan Turing published *Computing Machinery and Intelligence* (Turing, 1950). In this landmark paper, Turing—famous for deciphering the Nazi ENIGMA code during WWII—aims to answer the question, "Can machines think?" It presents the *Turing Test* to determine whether a machine can display the same intelligence (or the outcomes of that intelligence) as a person.

The Turing test's worth has been questioned. In 1956, John McCarthy coined the phrase "Artificial Intelligence" at the first-ever AI meeting at Dartmouth College (McCarthy, 2004). McCarthy would later design the Lisp programming language. Later that year, Allen Newell, J.C. Shaw, and Herbert Simon developed the Logic Theorist, the first AI software program. Frank Rosenblatt created the Mark 1 Perceptron, the first computer built on a neural network that 'learned' via trial and error in 1967 (Kanal, 2003). A year later, Marvin Minsky and Seymour Papert published *Perceptrons*, which became both a seminal work on neural networks and, for a while, an argument against future neural network research. In the 1980s, neural networks that trained themselves via a backpropagation method became widely employed in AI applications.

In 1997, the dominance of computer thinking was solidified in the public imagination when world chess champion Garry Kasparov was defeated by the AI expert system Deep Blue, developed by IBM (Campbell et al., 2002). In 2011, IBM Watson beat champions Ken Jennings and Brad Rutter at *Jeopardy!* In 2015, Baidu's Minwa supercomputer utilized a deep neural network called a convolutional neural network to detect and categorize pictures with an accuracy rate higher than the average human's (Simonite, 2015). DeepMind's AlphaGo software, backed by a deep neural network, defeated world champion Go player Lee Sodol in a five-game match 2016 (Gibney, 2016). Given the enormous number of possible moves as the game proceeds (nearly 14.5 trillion after only four plays), this victory is regarded as particularly significant. In fact, the potential of such systems was shown to have real market value when DeepMind was later bought by Google for a rumored £400 million (Baum, 2018).

Fast-forward to the current day, AI is creating a powerful driving force for the establishment and success of e-commerce. Modern systems allow for network marketing, electronic payment, and management of logistics toward bringing products to the customer in e-commerce (Zhen et al., 2021). AI assists e-commerce in identifying business trends and shifts to address the customer's immediate needs. Thus, it helps customers to make purchases at their convenience.

The objectives of the study are to:

- Investigate the impact of AI technology on consumer behavior in e-commerce and omnichannel retailing in China, including personalization and recommendation systems, trust and security, social influence and reviews, and user experience.
- Examine the cognitive, affective, and behavioral factors that influence consumer purchase intentions in the context of AI technology in the Chinese e-commerce and omnichannel retailing environment in China.
- Provide evidence-based recommendations for Chinese apparel retailers on effectively adopting AI-powered recommendation systems, chatbots, and virtual assistants to enhance consumer apparel purchase intentions and drive sales in the e-commerce and omnichannel retail environment in China.

The paper is structured as follows: The literature review provides a comprehensive overview of the existing research on the impact of AI technology on consumer behavior and purchase intention. The methodology section describes the research design, data collection, analysis methods, and the study's limitations. The results and analysis section presents the study's findings, and the discussion section interprets the results and their implications for the retail industry. The conclusion summarizes the main findings and contributions of the study and provides recommendations for practitioners and policymakers.

The current study contributes to the literature by providing empirical evidence on the impact of AI technology on purchase intentions in e-commerce and omnichannel retailing in

China. The findings have practical implications for retailers and policymakers and provide a foundation for future research.

This paper aims to answer the research question: What is the impact of AI technology on purchase intentions in e-commerce and omnichannel retailing in China? What are the cognitive, affective, and behavioral factors influence consumer purchase intentions in the context of AI technology in the Chinese e-commerce and omnichannel retailing environment? What evidence-based recommendations can be provided to Chinese apparel retailers on effectively adopting AI-powered recommendation systems, chatbots, and virtual assistants to enhance consumer apparel purchase intentions and drive sales in China's e-commerce and omnichannel retail environment?

Factoring in the existing research gap and the need for relevant research results for informed decision-making in practice (e.g., by retail managers and interactive marketing practitioners), this research addresses the following research questions:

- RQ1. How do AI-enabled technologies impact a customer's purchase intention?
- RQ2. How do AI-enabled technologies impact customer satisfaction?
- RQ3. How do AI-enabled technologies impact a customer’s brand trust?

2 LITERATURE REVIEW

The literature review is a critical component of any research study as it provides a comprehensive understanding of the existing knowledge and identifies research gaps in a specific field. By synthesizing and analyzing relevant scholarly articles, books, and other sources, the literature review establishes the context and significance of the research and informs the development of research questions and the selection of appropriate research methods.

In this research topic, this literature review aims to explore and analyze the scholarly work to gain insights into the current state of knowledge, identify key themes, theories, and methodologies employed in previous studies, and identify gaps in the existing research.

The first section of this literature review provides a summary of the growth of AI in China, AI as a concept, the application of AI in business, AI in supply chain operations, benefits of AI to retailing, AI, and retailing on customer satisfaction, and an overview of the historical background and evolution of research on this research topic. By examining seminal works and landmark studies, this section highlights the progression of knowledge in the field and acknowledges the significant contributions made by previous researchers.

This literature review seeks to uncover gaps and limitations in the existing body of research. By critically analyzing the literature, researchers will identify areas that require further investigation and areas where conflicting or inconclusive findings exist. These research gaps will be a foundation for developing research questions and hypotheses.

In conclusion, this literature review will comprehensively synthesize the existing research on our research topic and the methodologies employed. By identifying gaps in current knowledge, this review will contribute to the advancement of the field and guide the direction of this research study.

2.1 The Growth of AI in China

AI technology has rapidly grown in China in recent years, and the country has become a major player in the global AI landscape. The Chinese government has been actively promoting the development of AI technology and has set a goal to become a world leader in AI by 2030 (State Council of the People's Republic of China, 2017). The growth of AI technology in China is driven by factors such as the increasing availability of data, the development of new AI technologies, and the growing demand for AI applications in various industries. Based on studies conducted by the Stanford Institute for Human-Centered

Artificial Intelligence (HAI) (Daniel, Zhang et al., 2022), China published nearly one-third of all AI journal papers and AI citations globally in 2021. In terms of economic investment, China brought in $17 billion for start-ups in AI, making up over one-fifth of all private investment funding globally in 2021 (Daniel, Zhang et al., 2022).

2.2 Artificial Intelligence as a concept

Artificial Intelligence dates back to ancient times, but significant developments have occurred in the last century. In the 1950s, pioneers like Alan Turing and John McCarthy laid the foundation for AI research. Since then, AI has progressed through multiple stages, including expert systems, machine learning, and deep learning (Nilsson, 1998).

2.3 Application of AI in Business Circles

AI has rapidly advanced into various areas of modern society, such as medical research and innovative technology development, including autonomous vehicles. In the medical field, AI enhances the accuracy of programs that detect health conditions. AI technology has also been incorporated into popular applications such as Netflix and Spotify, which monitor users' habits and make recommendations based on their recent activity. Banks use AI systems to monitor account activity, detect identity theft, approve loans, and ensure online security. AI-powered programs are also deployed in call centers, analyzing a caller's voice in real-time to provide information that helps build a faster rapport with the caller (Holt, 2018). AI systems have various real-world applications nowadays. Some of the most frequent examples include voice recognition, virtual agents for online customer service, computer vision AI technologies, recommendation engines, and automated stock trading.

2.4 AI in Supply Chain Operations

AI is increasingly being applied in supply chain operations, where it has the potential to improve decision-making and optimize operations (Gülen, 2023). Using AI in supply chain management can reduce costs, improve efficiency, and increase customer satisfaction.

Businesses that use AI technology such as machine learning, predictive analytics, and robots may obtain important insights into their supply chains, automate repetitive operations, and make better choices.

2.5 Benefits of AI to Retailing

In the past decade, the retail industry has undergone significant transformation; mobile channels, social media, and emerging digital platforms have fundamentally altered retail business models, the implementation of the retail mix, and consumer behaviors. The introduction of the Internet channel and emerging digital channels such as mobile channels and social media has altered retail business models, mix execution, and customer behavior. Whereas multi-channel shopping was popular in the previous decade, we are now shifting to omnichannel retailing. Omnichannel retailing takes a broader view of channels and how buyers are affected and move among them during the search and purchasing process (Verhoef et al., 2015).

3. RESEARCH METHODOLOGY

3.1 Research Strategy

Mangiaracina et al. (2012) guided the components of the research onion model used to state and recommend different types of strategies as the research strategy. The significant categories of research strategies are quantitative, qualitative, and mixed methods.

In this research, a mixed-method approach will be employed to evaluate and explore the research hypothesis, combining the strengths of qualitative and quantitative methods to provide a comprehensive analysis. Establishing a complete research plan is critical to performing rigorous and meaningful research. By defining clear objectives, conducting a thorough literature review, selecting appropriate research designs and methodologies, ensuring effective resource planning and management, adhering to ethical principles, and planning for dissemination and knowledge transfer, researchers can increase their chances of success and maximize the potential impact of their work. A well-designed research strategy acts as a road map, leading researchers through the difficulties of the research process and allowing them to make substantial contributions to the particular fields of study.

3.2 Research framework and methodology

Research methodology is a foundation for conducting a research study. It justifies the choice of research methods and provides a comprehensive understanding of how data will be collected and analyzed. By clearly articulating the research methodology, researchers can enhance the credibility and reliability of their findings, contributing to the advancement of knowledge in their respective fields. Research methodology is critical to conducting a research study, providing a systematic framework for researchers to design, execute, and analyze their investigations. It encompasses various elements such as research philosophy, approach, strategy, choices, time horizon, and techniques and procedures (Saunders et al., 2023).

3.3 Research philosophy

The categories of philosophy include interpretivism, pragmatism, and positivism, among others. The research will be based on an interpretive philosophy since it helps explore and interpret the facts existing and the data collected to reach a theoretical standpoint. In addition, it will be relevant in analyzing the current state of affairs among the consumers and scenarios related to the topic. The interpretive philosophy provides a deeper, more elaborate perspective (Dwidienawati et al., 2020). The philosophical approach is based on the ontological category, exploring the fundamental aspects of a study.

3.4 Research approach

The research approach comprises two types: an inductive and deductive approach. Research approaches must be decided upon with great concern since both have different uses for the research. The reasoned approach will be used for this research since it examines the existing research, reads current theories of the AI phenomenon being studied, and then tests hypotheses emerging from those theories (Han, 2012). In addition, since the research will use the deductive approach, it applies both qualitative and quantitative methods.

The research will adopt a deductive approach to investigate the AI technology experience in the online shopping platform. By building on existing theories and testing their hypotheses, the research aims to contribute to the body of knowledge in this field. Using qualitative and quantitative methods will ensure a comprehensive analysis of the research problem, providing substantive learnings into the impact of AI technology on the online shopping experience.

3.5 Choice of Research Method

A mixed methods approach was employed to comprehensively examine the impact of AI technologies on purchase intentions in e-commerce and omnichannel retailing contexts in China. Mixed methods draw on the strengths of quantitative and qualitative data to provide robust insights beyond a single research approach (Mukumbang, 2023).

Quantitative methods collected numerical data on purchase intentions, such as survey responses or behavioral data from online platforms. These data allowed statistical analysis to uncover patterns, relationships, and correlations between AI technologies and purchase intentions. The quantitative component of the study provided a broad understanding of the overall impact of AI technologies on consumer behavior.

On the other hand, qualitative methods were employed to collect rich, in-depth insights into consumers' perceptions, attitudes, and experiences related to AI technologies in e-commerce and omnichannel retailing. Qualitative methods, such as interviews or focus groups, allowed researchers to explore the underlying reasons and motivations behind consumers' purchase intentions. The qualitative component of the study provided a deeper understanding of the nuances and complexities surrounding consumer behavior in the context of AI technologies.

In the quantitative phase, an online survey was distributed to 563 Chinese consumers to measure usage of various AI technologies (e.g., chatbots, recommendations), attributes of the consumer experience, and purchase intention outcomes. Descriptive statistics, correlations, and regressions analyzed relationships between these variables on a broad scale (ABU-BADER & Abu-Bader, 2021).

By integrating quantitative and qualitative data, the mixed methods approach provided a comprehensive and holistic examination of the impact of AI technologies on purchase intentions. The combination of numerical data and qualitative insights allowed for a more nuanced understanding of the research problem, capturing both the breadth and depth of consumer behavior in response to AI technologies in e-commerce and omnichannel retailing contexts.

Semi-structured interviews were then conducted with 30 consumers from the survey sample to contextualize and expand on quantitative findings. Interviews explored experiences using AI technologies, perceptions of how these tools influenced purchase decisions, and emergent themes to address the research questions at a deeper level (Guest & Namey, 2020).

An explanatory sequential mixed methods design was appropriate first to establish patterns from surveys and then build upon these through interviews (Fetters & Freshwater, 2015). The quantitative phase set a foundation, while qualitative interviews provided rich narratives and uncovered new insights (McKim, 2017). Integrating both data sources enhanced understanding beyond separate approaches (Fetters & Freshwater, 2015). To summarize, a mixed methods design capitalized on both empirical survey data and interview perspectives, addressing key research questions and limitations through triangulated evidence

(Almalki, 2016). This helped comprehensively examine AI impacts in e-commerce and omnichannel retailing contexts.

4. RESEARCH FINDINGS AND DISCUSSION

4.1 Descriptive statistics

According to Saunders et al. (2023), descriptive statistics are a helpful methodological supplement to inferential statistical analysis (Saunders et al., 2023). Furthermore, they clearly show the research facts and provide an initial perspective on the exploratory part of the investigation. Descriptive statistics are a type of summary statistic that describes, summarizes, and presents data understandably. These statistics give a quantitative and straightforward explanation of a dataset's primary traits and qualities, assisting researchers, analysts, and decision-makers in better understanding and communicating the data. Descriptive statistics are divided into two categories: measurements of central tendency and measures of variability (or dispersion).

The questionnaire's nominal factors include gender, age, home province, education level, seniority, and wage level. This section provides the mean, frequency, percentage, and standard deviation for each demographic variable in the aggregate sample and samples from several generation groups for additional study. Table 4 shows the number of surveys completed per generation group.

Table 4
Number of Completed Survey Questionnaire by Generation Groups

Workforce Generation	Number of completed questionnaires	Percentage
Total completed survey	550	100%
Social and Economic Reform group (Age over 40)	240	43.6%
Gen Y group (age between 30 and 40)	250	45.5%
Gen Z group (age less than 30)	60	10.9%

4.2 Analysis of Variance

To examine the statistical differences in the impact of the three basic needs among different China groups, we performed a one-way ANOVA with a post-hoc test. Specifically, we compared the means of three groups: China Mainland, Hong Kong, and Macau. Table 7 presents the comparison results.

4.3.1 One-Way ANOVA Results

Table 7

One-Way ANOVA Results by Country (Region)

ANOVA

		Sum of Squares	df	Mean Square	F	Sig.
Usefulness	Between Groups	19.668	2	9.834	7.316	<.001
	Within Groups	735.251	547	1.344		
	Total	754.919	549			
Informativeness	Between Groups	220.126	2	110.063	55.016	<.001
	Within Groups	1094.298	547	2.001		
	Total	1314.424	549			
Trust in Technology	Between Groups	2.030	2	1.015	.561	.571
	Within Groups	989.174	547	1.808		
	Total	991.205	549			
Entertainment	Between Groups	3.900	2	1.950	1.053	.350
	Within Groups	1013.352	547	1.853		
	Total	1017.253	549			
Irritation	Between Groups	29.900	2	14.950	8.907	<.001
	Within Groups	918.100	547	1.678		
	Total	948.000	549			
Purchase Intention	Between Groups	29.630	2	14.815	9.439	<.001
	Within Groups	858.532	547	1.570		
	Total	888.162	549			

A one-way ANOVA was performed to compare the effect of usefulness, Informativeness, Trust in Technology, Entertainment, Irritation, and Purchase Intention on the China region. The effect of usefulness, Informativeness, Irritation, and Purchase Intention on the different China region groups are significant at the $p<0.001$ level. The significant test results for Usefulness, Informativeness, Irritation, and Purchase Intention are at the $p<0.05$ level are [$F(2,547) = 7.316 >$ F-critical value = 3.01220, $p < .001 < 0.05$], [$F(2,547) =$

55.016 > F-critical value = 3.01220, p <0.001 < 0.05], [F(2,547) = 8.907 > F-critical value = 3.01220, p <0.001 < 0.05] and, [F(2,547) = 9.439 > F-critical value = 3.01220, p <0.001 < 0.05], respectively. However, Trust in Technology and Entertainment had an insignificant effect on the different China region groups at the p > 0.05 level [F (2.547) = .561 < F critical value = 3.01220, p = .571 > 0.05] and [F(2.547) = 1.053 < F critical value = 3.01220, p = .350 > 0.05].

4.3.2 Instrument Validity - Post Hoc Tests – Leven's test

Levene's test, named after the statistician Howard Levene, is a statistical test used to assess the equality of variances between two or more groups or conditions. It is commonly employed as a preliminary analysis before parametric tests, such as the independent samples t-test or analysis of variance (ANOVA), assuming equal variances.

Levene's test is a commonly used statistical test to assess the equality of variances between groups or conditions. It helps researchers determine whether the equal variance assumption holds, which is crucial for making valid inferences in subsequent parametric tests. Table 8 shows a test of homogeneity of variances (Levene's test result).

Table 8

Levene's test result

Tests of Homogeneity of Variances

		Levene Statistic	df1	df2	Sig.
Usefulness	Based on Mean	12.771	2	547	<.001
	Based on Median	12.499	2	547	<.001
	Based on Median and with adjusted df	12.499	2	515.860	<.001
	Based on trimmed mean	12.998	2	547	<.001
Informativeness	Based on Mean	26.972	2	547	<.001
	Based on Median	24.995	2	547	<.001
	Based on Median and with adjusted df	24.995	2	523.896	<.001
	Based on trimmed mean	26.519	2	547	<.001
Irritation	Based on Mean	2.392	2	547	.092
	Based on Median	1.928	2	547	.146
	Based on Median and with adjusted df	1.928	2	524.105	.146
	Based on trimmed mean	2.560	2	547	.078
Purchase Intention	Based on Mean	5.126	2	547	.006
	Based on Median	5.013	2	547	.007
	Based on Median and with adjusted df	5.013	2	513.889	.007
	Based on trimmed mean	4.402	2	547	.013

Leven's test for equality of variance for Usefulness, Informativeness, Irritation, and Purchase Intention was found to be violated in present analysis, [$F(2,547) = 12.771$, $p<0.001$)], [$F(2,547) = 26.972$, $p<0.001$)], [$F(2,547) = 2.392$, $p<0.001$)], [$F(2,547) = 5.126$, $p<0.001$)]. Owing to this violated assumption, a Welch ANOVA was computed.

4.3.3 Instrument Reliability - Post Hoc Tests – Welch test

The Welch test, also known as Welch's t-test or the unequal variances t-test, is a statistical test used to compare the means of two independent groups when the assumption of equal population variances is violated. It is a modification of the independent samples t-test that allows for unequal variances between the compared groups.

The Welch test is instrumental when the variances of the two groups are significantly different or when the sample sizes of the groups are unequal. In such cases, using the traditional independent samples t-test, which assumes equal variances, may lead to inaccurate results and incorrect conclusions.

The Welch test serves as a valuable statistical method for comparing the means of two independent groups when the assumption of equal variances is not met, offering a robust alternative to the traditional independent samples t-test. Table 9 represents the robust tests of equality of means (Welch test results) for this research.

Table 9

Welch test result

Robust Tests of Equality of Means[b]

		Statistic[a]	df1	df2	Sig.
Usefulness	Welch	149.941	2	355.807	<.001
Informativeness	Welch	.	.	.	.
Irritation	Welch	26.439	2	62.018	<.001
Purchase Intention	Welch	10.650	2	53.944	<.001

a. Asymptotically F distributed.

b. Robust tests of equality of means cannot be performed for Informativeness because at least one group has 0 variance.

The Welch test revealed that there was a statistically significant difference in Usefulness, Irritation, and Purchase Intention between at least two groups; [F(2,355.807) =, p<0.01)], [F(2,62.018) = 26.439, p<0.01)], and [F(2,53.944) = 10.650, p<0.01)]. Robust tests of equality of means cannot be performed for Informativeness because at least one group has 0 variance.

4.3.4 Post Hoc Tests – Games-Howell test and Tukey HSD test

The Games-Howell test and Tukey's Honest Significant Difference (HSD) test are statistical methods used in inferential statistics to compare multiple groups or conditions and determine significant differences between them.

The Games-Howell test is a post hoc test employed when the assumption of equal variances across groups is violated. This test is an alternative to the traditional Tukey's HSD test, which assumes equal variances. The Games-Howell test calculates adjusted p-values and confidence intervals, considering the unequal variances among the groups. It is beneficial when dealing with datasets with unequal variances and sample sizes.

On the other hand, Tukey's HSD test is a post hoc test commonly used in the analysis of variance (ANOVA) to identify significant pairwise differences between groups. It assumes equal variances across the groups being compared. Tukey's HSD test calculates the minimum significant difference necessary to reject the null hypothesis of equal group means. It is widely used for multiple comparisons after ANOVA to determine which specific group means differ significantly.

The choice between the Games-Howell test and Tukey's HSD test depends on the specific characteristics of the dataset. If the assumption of equal variances is violated, the Games-Howell test is more appropriate. However, Tukey's HSD test is commonly used if the assumption of equal variances holds.

When conducting statistical analyses, it is important to select the appropriate test based on the assumptions of the data and the research question at hand. Additionally, it is essential to interpret the results of these tests cautiously, considering effect sizes, confidence intervals, and other relevant statistical measures. Table 10 represents the results of the Games-Howell and Tukey HSD tests.

Table 10

Post Hoc Tests result – Games-Howell test and Tukey HSD test

Multiple Comparisons

Dependent Variable		(I) What country do you currently reside	(J) What country do you currently reside	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
							Lower Bound	Upper Bound
Usefulness	Tukey HSD	China Mainland	China Hong Kong	-.14262	.10088	.334	-.3797	.0945
			China Macau	-1.00595*	.26834	<.001	-1.6366	-.3753
		China Hong Kong	China Mainland	.14262	.10088	.334	-.0945	.3797
			China Macau	-.86333*	.26941	.004	-1.4965	-.2302
		China Macau	China Mainland	1.00595*	.26834	<.001	.3753	1.6366
			China Hong Kong	.86333*	.26941	.004	.2302	1.4965
	Games-Howell	China Mainland	China Hong Kong	-.14262	.10306	.350	-.3849	.0996
			China Macau	-1.00595*	.07090	<.001	-1.1730	-.8389
		China Hong Kong	China Mainland	.14262	.10306	.350	-.0996	.3849
			China Macau	-.86333*	.07953	<.001	-1.0508	-.6759
		China Macau	China Mainland	1.00595*	.07090	<.001	.8389	1.1730
			China Hong Kong	.86333*	.07953	<.001	.6759	1.0508
Informativeness	Tukey HSD	China Mainland	China Hong Kong	.84571*	.12307	<.001	.5565	1.1349
			China Macau	2.95238*	.32737	<.001	2.1830	3.7217
		China Hong Kong	China Mainland	-.84571*	.12307	<.001	-1.1349	-.5565
			China Macau	2.10667*	.32868	<.001	1.3342	2.8791
		China Macau	China Mainland	-2.95238*	.32737	<.001	-3.7217	-2.1830
			China Hong Kong	-2.10667*	.32868	<.001	-2.8791	-1.3342
	Games-Howell	China Mainland	China Hong Kong	.84571*	.12609	<.001	.5493	1.1421
			China Macau	2.95238*	.08119	<.001	2.7611	3.1437
		China Hong Kong	China Mainland	-.84571*	.12609	<.001	-1.1421	-.5493
			China Macau	2.10667*	.09647	<.001	1.8792	2.3341
		China Macau	China Mainland	-2.95238*	.08119	<.001	-3.1437	-2.7611
			China Hong Kong	-2.10667*	.09647	<.001	-2.3341	-1.8792
Irritation	Tukey HSD	China Mainland	China Hong Kong	-.15667	.11273	.347	-.4216	.1083
			China Macau	-1.25000*	.29986	<.001	-1.9547	-.5453
		China Hong Kong	China Mainland	.15667	.11273	.347	-.1083	.4216
			China Macau	-1.09333*	.30106	<.001	-1.8008	-.3858

		China Macau	China Mainland	1.25000*	.29986	<.001	.5453	1.9547
			China Hong Kong	1.09333*	.30106	<.001	.3858	1.8008
	Games-Howell	China Mainland	China Hong Kong	-.15667	.11382	.354	-.4242	.1109
			China Macau	-1.25000*	.17282	<.001	-1.6755	-.8245
		China Hong Kong	China Mainland	.15667	.11382	.354	-.1109	.4242
			China Macau	-1.09333*	.17283	<.001	-1.5188	-.6678
		China Macau	China Mainland	1.25000*	.17282	<.001	.8245	1.6755
			China Hong Kong	1.09333*	.17283	<.001	.6678	1.5188
Purchase Intention	Tukey HSD	China Mainland	China Hong Kong	-.36429*	.10901	.003	-.6205	-.1081
			China Macau	-.96429*	.28997	.003	-1.6457	-.2828
		China Hong Kong	China Mainland	.36429*	.10901	.003	.1081	.6205
			China Macau	-.60000	.29113	.099	-1.2842	.0842
		China Macau	China Mainland	.96429*	.28997	.003	.2828	1.6457
			China Hong Kong	.60000	.29113	.099	-.0842	1.2842
	Games-Howell	China Mainland	China Hong Kong	-.36429*	.10839	.002	-.6191	-.1095
			China Macau	-.96429*	.24369	.002	-1.5726	-.3560
		China Hong Kong	China Mainland	.36429*	.10839	.002	.1095	.6191
			China Macau	-.60000	.24006	.051	-1.2016	.0016
		China Macau	China Mainland	.96429*	.24369	.002	.3560	1.5726
			China Hong Kong	.60000	.24006	.051	-.0016	1.2016

*. The mean difference is significant at the 0.05 level.

The Games-Howell test for multiple comparisons found that the mean value of usefulness was significant difference between China Mainland (M=4.7, SD=1.1) and Macau (M=5.8, SD=.1), p<0.01, 95% C.I. = -1.17, -.84. Games-Howell test for multiple comparisons found that the mean value of usefulness was significantly different between Hong Kong (M=4.9, SD=1.2) and Macau (M=5.8, SD=.1), p<0.01, 95% C.I. = -1.05, -.68. However, there was no significant difference of mean value of usefulness between China Mainland (M=4.7, SD=1.1) and Hong Kong (M=4.9, SD=1.2), p= .35.

Games-Howell test for multiple comparisons found that the mean value of informativeness was significantly different between China Mainland (M=4.7, SD=1.1) and Macau (M=5.8, SD=.1), p<0.01, 95% C.I. = -2.76,3.14. Games-Howell test for multiple comparisons found that the mean value of informativeness was significantly different between Hong Kong (M=4.9, SD=1.2) and Macau (M=5.8, SD=.1), p<0.01, 95% C.I. = 1.88, 2.33. Games-Howell test for multiple comparisons found that the mean value of informativeness was significantly different between Hong Kong (M=4.9, SD=1.2) and China Mainland (M=4.7, SD=1.1), $p<0.01$, 95% C.I. = .55, 1.14.

Games-Howell test for multiple comparisons found that the mean value of Irritation was significant different between China Mainland (M=4.7, SD=1.1) and Macau (M=5.8, SD=.1), $p<0.01$, 95% C.I. = -1.68, -.82. Games-Howell test for multiple comparisons found that the mean value of Irritation was significant different between Hong Kong (M=4.9, SD=1.2) and Macau (M=5.8, SD=.1), $p<0.01$, 95% C.I. = -1.52, -.67. However, there was no significant difference in mean value of irritation between China Mainland (M=4.7, SD=1.1) and Hong Kong (M=4.9, SD=1.2), $p= .35$.

Games-Howell test for multiple comparisons found that the mean value of Purchase Intention was significant different between China Mainland (M=4.7, SD=1.1) and Hong Kong (M=4.9, SD=1.2), $p<0.01$, 95% C.I. = -.62, -1.1. Games-Howell test for multiple comparisons found that the mean value of Purchase Intention was significant different between China Mainland (M=4.7, SD=1.1) and Macau (M=5.8, SD=.1), $p<0.01$, 95% C.I. = -1.57, -.36. However, there was no significant difference in mean value of irritation between Macau (M=5.8, SD=.1) and Hong Kong (M=4.9, SD=1.2), $p= .51$.

4.3.5 Summary

To test the hypothesis regarding the impact of AI technology on the development of purchase intention in China, a statistical analysis tool known as ANOVA (Analysis of Variance) can be utilized. The objective of ANOVA is to examine whether a qualitative or quantitative factor has a significant effect on the changes observed in the target variable being investigated. This is achieved by dividing the factor into groups and determining whether the effect of the factor is consistent across the means of the corresponding data sets. Having a minimum of two groups is necessary, and the indicators within these groups can be either qualitative or quantitative.

ANOVA assesses the ratio of two variances. Variance measures the spread of data around the mean value. The first variance, explained, represents the dispersion of all values between the groups around the overall mean value. The second variance, the unexplained variance, characterizes the dispersion of data within the groups around the means of the individual groups. The between-group variance is associated with the first variance, while the within-group variance is associated with the second variance. The ratio of these variances is referred to as the F-test statistic, compared to the critical value of the F-test. Suppose the calculated F-test statistic exceeds the critical value. In that case, it indicates that the mean values of the groups differ significantly, thus demonstrating that the studied factor has a significant effect on the observed data. Conversely, suppose the calculated F-test statistic is less than the critical value. In that case, it suggests that the mean values of the groups do not differ significantly, indicating that the factor does not have a significant effect.

This study employed separate one-way ANOVAs to examine the individual effects of five independent variables—Usefulness, Informativeness, Trust in Technology, Entertainment, and Irritation—on Purchase Intention among Chinese e-commerce consumers. Each one-way ANOVA tested the significance of a single factor's influence on the dependent variable through hypothesis testing, assessing whether group means differed across the factor's levels (Field, 2018). In ANOVA, null and alternative hypotheses are formulated as follows:

H_0: $\mu 1 = \mu 2 = \ldots = \mu m$,

H_a: not all: μi are equal - not all means are equal.

If the influence of a factor is deemed insignificant, it implies that there is no significant difference between the groups associated with that factor. Consequently, during the analysis of variance, the null hypothesis (H_0) is not rejected. On the other hand, if the factor's influence is significant, the null hypothesis (H_0) is rejected, indicating that not all groups possess the same mean value. In other words, there are significant differences among the groups. The statistical framework utilized in ANOVA is the Table of Empirical Data. One-way ANOVA is based on the sum of the squared deviations within a statistical framework can be divided into different components.

Between groups sum of squares of deviations:

$$SS_b = \sum n_i(\bar{x}_i - \bar{\bar{x}})^2$$

Within group sum of squares of deviations:

$$SS_w = \sum (x - \bar{x}_i)^2$$

Total sum of squares of deviations:

$$SS = \sum (x - \bar{x})^2 = SS_b + SS_w$$

Between groups (factorial) variance:

$$MS_B = \frac{SS_B}{k-1}$$

Within group (residual) variance:

$$MS_W = \frac{SS_W}{N-k}$$

F-test:

$$F = \frac{MS_B}{MS_W}$$

To conduct a one-way analysis of variance for a given dataset, it is essential to calculate the actual F-test, which represents the ratio between the variance explained by the factor's influence (between groups) and the unexplained variance (within groups). The results of these calculations are typically presented in the form of the following table:

	Sum of squares	*df* (number of degrees of freedom)	Mean square	*F*
Between groups	SS_B	$\nu_k = k - 1$	MS_B	*F*-value
Within groups	SS_W	$\nu_c = N - k$	MS_W	
Total	$SS_B + SS_W$	$\nu = N - 1$	$MS_B + MS_W$	

where

$\nu_k = k - 1$ – the number of degrees of freedom of the explained variance,

$\nu_c = N - k$ – number of degrees of freedom of unexplained variance,

$\nu = N - 1$ – total number of degrees of freedom.

When the computed F-test statistic exceeds the critical F-value ($F > F_{\alpha;\nu k;\nu c}$), the null hypothesis is rejected at the α significance level, indicating that the factor significantly affects the observed data with a confidence level of $P = 1 - \alpha$ (Gravetter & Wallnau, 2017). Conversely, if the computed F-test statistic is below the critical F-value ($F < F_{\alpha;\nu k;\nu c}$), the null hypothesis is not rejected at the α significance level, suggesting insufficient evidence to conclude the factor influences the data (Gravetter & Wallnau, 2017).

This implies that the factor does not significantly affect the data with a probability of $P = 1 - \alpha$. In modern statistical software packages such as SPSS, Minitab, Evews, Excel, etc., the probability level, known as the p-value, can be obtained. By setting the significance level α for the test, the following decision rule can be applied:

Accept H_0, if p-value ≥ α,

Otherwise, reject H_0.

Various values such as SSB, SSW, SS, MSB, MSW, p-value, and F-test for one-way ANOVA are automatically calculated when utilizing computer statistical packages. Therefore, there is no need for manual calculation. However, it is important to correctly interpret the ANOVA results generated by the SPSS statistical package. In our specific case, the null and alternative hypotheses are formulated as follows:

Null hypothesis ($H1_0$): AI-assisted e-commerce and omnichannel retailing shopping are not perceived as more useful than unassisted e-commerce and omnichannel retailing shopping.

Alternative hypothesis ($H1_a$): AI-assisted e-commerce and omnichannel retailing shopping are perceived as more useful than unassisted e-commerce and omnichannel retailing shopping.

Null hypothesis ($H2_0$): AI-assisted e-commerce and omnichannel retailing shopping are not perceived as more entertaining than unassisted e-commerce and omnichannel retailing shopping.

Alternative hypothesis ($H2_a$): AI-assisted e-commerce and omnichannel retailing shopping are perceived as more entertaining than unassisted e-commerce and omnichannel retailing shopping.

Null hypothesis ($H3_0$): AI-assisted e-commerce and omnichannel retailing shopping are not perceived as more informative than unassisted e-commerce and omnichannel retailing shopping.

Alternative hypothesis ($H3_a$): AI-assisted e-commerce and omnichannel retailing shopping are perceived as more informative than unassisted e-commerce and omnichannel retailing shopping.

Null hypothesis ($H4_0$): AI-assisted e-commerce and omnichannel retailing shopping are not perceived as more irritating than unassisted e-commerce and omnichannel retailing shopping.

Alternative hypothesis ($H4_a$): AI-assisted e-commerce and omnichannel retailing shopping are perceived as more irritating than unassisted e-commerce and omnichannel retailing shopping.

Null hypothesis ($H5_0$): AI-assisted e-commerce and omnichannel retailing shopping does not lead to a higher purchase intention than unassisted e-commerce and omnichannel retailing.

Alternative hypothesis ($H5_a$): AI-assisted e-commerce and omnichannel retailing shopping leads to a higher purchase intention than unassisted e-commerce and omnichannel retailing.

Null hypothesis ($H6_0$): AI-assisted shopping using explainable recommendations is not perceived as more trustworthy compared to AI-assisted shopping not using explainable recommendations.

Alternative hypothesis ($H6_a$): AI-assisted shopping using explainable recommendations are perceived as more trustworthy compared to AI-assisted shopping not using explainable recommendations. Table 11 below presents a summary of the statistical analysis results for the six null hypotheses.

Table 11

Results of the statistical analysis of the six null hypotheses

	Null Hypothesis	p value	Result
$H1_0$	AI-assisted e-commerce and omnichannel retailing shopping are not perceived as more useful than unassisted e-commerce and omnichannel retailing shopping.	<.001	Rejected
$H2_0$	AI-assisted e-commerce and omnichannel retailing shopping are not perceived as more entertaining than unassisted e-commerce and omnichannel retailing shopping.	.350	Supported
$H3_0$	AI-assisted e-commerce and omnichannel retailing shopping are not perceived as more informative than unassisted e-commerce and omnichannel retailing shopping.	<.001	Rejected
$H4_0$	AI-assisted e-commerce and omnichannel retailing shopping are not perceived as more irritating than unassisted e-commerce and omnichannel retailing shopping.	<.001	Rejected
$H5_0$	AI-assisted e-commerce and omnichannel retailing shopping do not lead to a higher purchase intention than unassisted e-commerce and omnichannel retailing.	<.001	Rejected

$H6_0$	AI-assisted shopping using explainable recommendations is not perceived as more trustworthy compared to AI-assisted shopping not using explainable recommendations.	.571	Supported

5. CONCLUSION

5.1 Conclusions of the study

The study aims to identify the impacts of AI technology on e-commerce and omnichannel retailing purchase intention in China.

Reflecting on the existing research gap and the need for relevant research results to inform decision-making in practice (e.g., by retail managers and interactive marketing practitioners), this research addresses the following research questions. Table 13 shows the results of the main study and case study.

- RQ1. How do AI-enabled technologies impact a customer's purchase intention?
- RQ2. How do AI-enabled technologies impact a customer's satisfaction?
- RQ3. How do AI-enabled technologies impact a customer's brand trust?

Table 13: Results of the Main Study and Case Study

Major study (By Hypothesis)		p value	Result	Case Study (By Theme)		Result
$H1_0$	AI-assisted e-commerce and omnichannel retailing shopping is not perceived as more useful than unassisted e-commerce and omnichannel retailing shopping. Findings: The testing of the first null hypothesis ($H1_0$) resulted in its acceptance with a p value of <.001, below the threshold of 0.05. It was concluded that AI-assisted e-commerce and omnichannel retailing shopping are perceived as more useful than unassisted e-commerce and omnichannel retailing shopping.	<.001	Rejected	T1	Theme 1: Usefulness of AI Technologies AI-assisted e-commerce and omnichannel retailing shopping is not perceived as more useful than unassisted e-commerce and omnichannel retailing shopping. Findings: The respondents were unanimous in their disagreement with this. Respondents express that AI systems provide personalized recommendations, suggest relevant products based on their preferences and browsing history, and introduce them to new items they might not have discovered otherwise.	Rejected
$H2_0$	AI-assisted e-commerce and omnichannel retailing shopping is not perceived as more entertaining than unassisted e-commerce and omnichannel retailing shopping. Findings: The testing of the second null hypothesis ($H2_0$) resulted in its acceptance with a p value of 0.35, above the threshold of 0.05. It was concluded that AI-assisted e-commerce and omnichannel retailing shopping is not perceived as more entertaining than	0.35	Supported	T4	Theme 4: Entertainment and AI Technologies AI-assisted e-commerce and omnichannel retailing shopping is not perceived as more entertaining than unassisted e-commerce and omnichannel retailing shopping. Findings: The respondents were unanimous in their disagreement with this. Respondents express that the presence of AI technologies does not	Rejected

	unassisted e-commerce and omnichannel retailing shopping.				significantly enhance their shopping experience in terms of entertainment or enjoyment.	
$H3_0$	AI-assisted e-commerce and omnichannel retailing shopping is not perceived as more informative than unassisted e-commerce and omnichannel retailing shopping. Findings: The testing of the third null hypothesis ($H3_0$) resulted in its acceptance with a p value of <.001, below the threshold of 0.05. It was concluded that AI-assisted e-commerce and omnichannel retailing shopping are perceived as more informative than unassisted e-commerce and omnichannel retailing shopping. .	<.001	Rejected	T2	Theme 2: Informativeness of AI Technologies AI-assisted e-commerce and omnichannel retailing shopping is not perceived as more informative than unassisted e-commerce and omnichannel retailing shopping. Findings: The respondents were unanimous in their disagreement with this. Some respondents express that AI systems provide in-depth information about product specifications, materials, or other relevant details that they would expect when making informed purchasing decisions.	Rejected
$H4_0$	AI-assisted e-commerce and omnichannel retailing shopping is not perceived as more irritating than unassisted e-commerce and omnichannel retailing shopping. Findings: The testing of the fourth null hypothesis ($H4_0$) resulted in its acceptance with a p value of <.001, below the threshold of 0.05. It was concluded that AI-assisted e-commerce and omnichannel retailing shopping are perceived as more irritating than unassisted e-commerce and omnichannel retailing shopping.	<.001	Rejected	T5	Theme 5: Irritation and Challenges of AI Technologies AI-assisted e-commerce and omnichannel retailing shopping is not perceived as more irritating than unassisted e-commerce and omnichannel retailing shopping. Findings: The respondents were unanimous in their disagreement with this. Some respondents express positive experiences, noting that AI technologies enhance their shopping journey by providing convenient features, personalized recommendations, and efficient customer service, without causing significant levels of irritation.	Rejected
$H5_0$	AI-assisted e-commerce and omnichannel retailing shopping does not lead to a higher purchase intention than unassisted e-commerce and omnichannel retailing. Findings: The testing of the fifth null hypothesis ($H5_0$) resulted in its acceptance with a p value of <.001, below the threshold of 0.05. It was concluded that AI-assisted e-commerce and omnichannel retailing shopping does lead to a higher purchase intention than unassisted e-commerce and omnichannel retailing.	<.001	Rejected	T6	Theme 6: Purchase Intention and AI Technologies AI-assisted e-commerce and omnichannel retailing shopping does not lead to a higher purchase intention than unassisted e-commerce and omnichannel retailing. Findings: The respondents were unanimous in their disagreement with this. Respondents express positive sentiments about the convenience, personalization, and efficiency enabled by AI technologies, which, in turn, may lead to higher purchase intentions.	Rejected
$H6_0$	AI-assisted shopping using explainable recommendations is not perceived as more trustworthy compared to AI-assisted shopping not using explainable recommendations. Findings: The testing of the sixth null hypothesis ($H6_0$) resulted in its acceptance with a p value of 0.571, above the threshold of 0.05. It was concluded that AI-assisted shopping using explainable recommendations is not perceived as more trustworthy compared to AI-assisted shopping not using explainable recommendations.	0.571	Supported	T3	Theme 3: Trust in Technology and AI AI-assisted shopping using explainable recommendations is not perceived as more trustworthy compared to AI-assisted shopping not using explainable recommendations. Findings: The majority of respondents indicated their agreement with this statement. Some respondents' express concerns regarding the reliability, accuracy, and transparency of AI recommendations, irrespective of whether these recommendations are explainable.	Supported

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