Exploring Students' Continuence Intention Toward Artificial Intelligence

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ABSTRAK

Various forms of artificial intelligence (AI), including machine-driven AI, cognitive AI, and emotional AI, collaborate to provide numerous advantages in marketing research and help marketers develop effective strategies. This study utilized the Technology Acceptance Model (TAM) to investigate the factors that motivate students to continue utilizing AI in marketing research. In order to achieve the study's objectives, we employed quantitative methods to pinpoint the applications of AI in marketing research. A questionnaire survey was distributed to 200 student respondents to collect data. Importance Performance Map Analysis (IPMA) scrutinizes the collected data. The study assesses the significance of AI in marketing research among students, revealing that attitude significantly impacts the committed to keep utilizing AI. Perceived usefulness, the most critical factor, strongly links positive attitudes to continued usage, suggesting users perceive AI as enhancing their experiences. Acceptance of AI is also influenced by perceived ease of use, system, information, and service quality, as well as attitude. The results indicate that efficient system operation, improved information quality, and high-quality systems and services foster positive perceptions and preferences for AI. The results of this study offer valuable insights for educators in higher education, guiding them on effective strategies to encourage their students to utilize AI in a responsible manner, particularly within the realm of marketing research.

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Exploring Students' Continuence Intention Toward Artificial Intelligence

1. Introduction

A new era of autonomous digital content creation has been began since recent years as many adopt Artificial intelligence (AI) systems in various sectors, such as business (Weber & Schütte, 2019), public organizations (Neumann et al, 2024), and educations (Al-Qaysi et al., 2024). Through the use of extensive training data or large datasets from algorithms (Weber & Schütte, 2019) , AI systems are designed to think and act like humans, performing tasks that typically require human intelligence or making rational decisions based on logic and thorough consideration of all options (Neumann et al., 2024). With its outstanding capability of partially or wholly replacing humans in the performance of tasks, many predict AI might outperform humans (Neumann et al., 2024).

Higher education institutions recognize opportunities to employ AI throughout students' learning process, beyond assessment purposes only (Strzelecki, 2023). It is because AI has diverse capabilities not only for digital content creation (e.g. image, text, music, video, and data augmentation) but also for brainstorming, summarization, and refining feedback phrasing, which may provide personalized tutoring services for better students' learning processes (Al-Qaysi et al., 2024; Lo, 2023). Its impact is proven in a study by (Weber & Schütte, 2019), where students find their learning outcomes increase after utilizing AI during their studies. This may be explained by (Nazari, Shabbir, & Setiawan, 2021) as they find AI could provide formative and immediate feedback for students, which is often delayed too long if they expect from teachers. AI's real-time feedback motivates students to be more engaged, develop their knowledge, and become active and independent learners (Nazari et al., 2021).

The function of AI expands to academic research; which students undertake as a part of their learning process. Research may be challenging for most higher education students since they can find hurdles in any research stage, such as reviewing abundant literature systematically, formulating research problems, designing the correct methodology, and evaluating the results of data analysis (Karunananda et al, 2021). Throughout the entire research process, AI can serve researchers the best when they must deal with many kinds of literature to review, as it will be time-consuming and likely to be error-prone (Salleh, 2023). AI effectively summarises a large body of literature and benefits researchers by balancing scholarly efforts, saving time, and reducing errors (Salleh, 2023). AI benefits researchers as it complements scholarly efforts, saves time and reduces errors. In addition, AI has been widely employed in R&D settings, such as lab education (Guayta, 2021) and engineering lab training (Estrada, Paheding, Yang, & Niyaz, 2022).

Although AI is superior in efficiently solving complex problems using data and time effectively (Lund & Wang, 2023), some people still feel troubled by AI's threats in the education sector. Certain educational institutions opt to prohibit students from using ChatGPT in order to prevent them from relying on it to complete their assignments, given its capacity to quickly produce satisfactory written content and offer precise responses to user inquiries (Lo, 2023). In other words, the presence of AI is likely to impede the ability to think critically and creatively, increase dependence on such technologies, and reduce human adaptability and innovation. Without strong self-awareness, students may be vulnerable to plagiarism and inaccuracy issues while using AI (Lo, 2023). Even the common issue of AI is accessing unauthorized data, overlooking data ownership to give the best response to every question of users (Neumann et al., 2024).

These challenges and threats have made some people reluctant to adopt AI for education (Lo, 2023; Lund & Wang, 2023). Some universities prefer to ban students' access to ChatGPT to avoid outsourcing the work to ChatGPT, which can quickly generate acceptable texts and provide specific answers to users' questions (Dwivedi et al., 2023). However, there are still few studies analyzing students' standpoints toward AI application, though theirs are as necessary as the viewpoints of other stakeholders in higher education (Strzelecki, 2023). Farhi et al., (2023) identified that along with the benefits of AI for students, some serious concerns about AI also grow among them and are likely to inhibit them from fully adopting it, for instance, concerns regarding unethical utilization, extreme dependence, and reduced writing and cognitive abilities could come up, as similar to threats as mentioned earlier.

Based on this, this study strives to answer a research gap in students' acceptance of AI, particularly for research activities among marketing students. While the perspectives of students are just as essential as those of other stakeholders in higher education, this research differs from past studies in that it makes an effort to analyze students' perspectives on the deployment of AI. According to (Huang & Rust, 2021), several types of AI, namely machine-driven AI, cognitive AI, and emotional AI, work together, offering multiple benefits in marketing research and serving strategically for marketers to determine their effective strategies. This study aims to utilize the Technology Acceptance Model (TAM) to investigate what drivers affect students' continuance intention toward AI for marketing research. Then, it is expected that the findings will shed light on how educators in higher education can encourage their students to utilize AI, especially in a marketing research context.

Artificial Intelligence in Marketing Research

Previous research findings have shown that incorporating AI into marketing provides numerous advantages, including enhanced personalization, greater efficiency, and improved decision-making (Kumar, 2021; Nazari et al., 2021). The research also discovered that artificial intelligence (AI) greatly influences consumer behavior and attitudes, particularly through personalized recommendations. In expansion, moral contemplations related with the utilize of AI in showcasing were moreover distinguished, counting issues of straightforwardness, responsibility, and decency.

In conclusion, AI plays a critical part within the analysis of research data by improving pattern recognition, enabling predictive modeling and facilitating language or text data processing. Its integration has improved the efficiency and accuracy of data analysis significantly in various research domains.

Technology Acceptance (TAM) Model

Given the ever-changing landscape of technology, future studies could concentrate on applying the TAM Model to emerging technologies like artificial intelligence, virtual reality, and block chain technology and its application in marketing (Musa, Fatmawati, Nuryakin, & Suyanto, 2024). In the context of AI, TAM can be used to explore how individuals perceive The moral considerations linked to making decisions relying on data. Scholars are investigating the fine line between providing personalized suggestions and addressing privacy issues, highlighting the importance of transparent AI algorithms and consent procedures (Kronemann, Kizgin, Rana, & K. Dwivedi, 2023; Moradi, 2021). These investigations align with ongoing discussions on data privacy and offer practical guidance for responsibly incorporating AI into marketing research (Davenport et al, 2020; Malgieri, 2023).

System Quality

System quality, as used in technology, refers to a collection of critical attributes that provide information, including technical sufficiency, latency, navigation, display, privacy, and security (Baker-Eveleth & Stone, 2020; Gupta et al, 2021). Earlier research into technology adoption has demonstrated a notable link between system quality and the perceived ease of use and usefulness (Na et al, 2022; Vanduhe, Nat, & Hasan, 2020). Consequently, the subsequent hypotheses are put forth:

H1. System Quality significantly affect Perceived ease of use

H2. System Quality significantly affect Perceived usefulness

Information Quality

Previous studies found that information quality is strongly connected to usefulness and ease of use, with high quality and ease of use promoting a sustained intention to utilize the online banking service (Ghasemaghaei & Hassanein, 2019; Montazemi & Qahri-Saremi, 2015). Therefore, it is hypothesized:

H3. Information quality significantly influence Perceived ease of use

H4. Information quality significantly influence Perceived usefulness

Service Quality

Perceived service quality, encompassing timely service, prompt responses to consumer needs, personalized service, and professional service, also significantly impacts perceived ease of use and perceived usefulness (Azzahra & Kusumawati, 2023; Hanjaya et al, 2019). Hence, the following hypotheses are put forward.

H5. Service Quality significantly impact on Perceived ease of use

H6. Service Quality significantly impact on Perceived usefulness

Attitudes

In the Technology Acceptance Model (TAM), it is suggested that the perceived ease of use and perceived Usefulness influences both attitude and behavioral intention to use a particular technology (Foroughi et al, 2019; Na et al., 2022; Tam, Santos, & Oliveira, 2020). Consequently, we posit the following hypothesis:

H7. Perceived ease of use significantly affect Attitude

H8. Perceived usefulness significantly affect Attitude

H9. Attitude significantly affect Continuance Intention

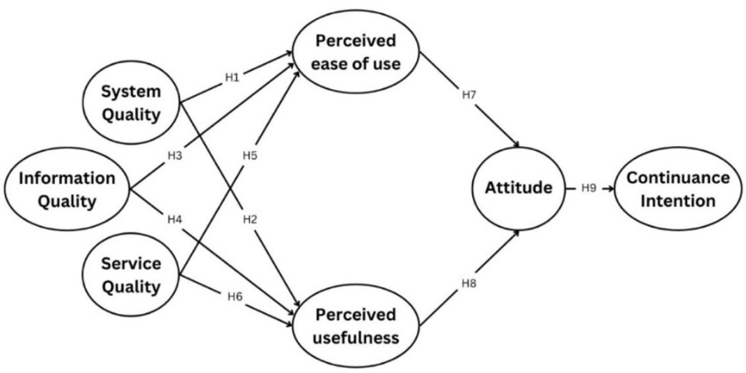

Figure 1. The conceptual Model

2. Research Methodology

In order to accomplish the objectives of the study., the researchers employed quantitative methods to pinpoint the application of AI in marketing research. This study employed a questionnaire survey with 200 students as respondents in order to obtain data. Through quantitative analysis, the extent of AI's importance in marketing research becomes clear. Prior to the survey, a questionnaire consisting of 33 questions (using a five-point Likert scale) was created to represent the seven factors (system quality, information quality, service quality, perceived ease of use, perceived usefulness, attitudes, continuance intention) outlined in the model. Adjustments were made, and the questions were derived from these variables by consulting previous studies (Ashfaq, Yun, Yu, & Loureiro, 2020; Jo, 2023; Kasuma et al., 2020). Questionnaires were administered to students who had completed marketing research courses. The survey was carried out online between March and May 2024.

The collected data is analyzed using Importance Performance Map Analysis (IPMA). The IPMA, also referred to as the priority map analysis, importance-performance matrix, or impact-performance map, is a widely recognized tool in the field of project management (Ringle & Sarstedt, 2016) is a valuable technique applied within Partial Least Squares Structural Equation Modeling (PLS-SEM). Two of IPMA's primary objectives are to ascertain which variable constructs are comparatively significant and how effectively each works (Teeluckdharry, et al, 2022; Yapp & Yeap, 2023). The IPMA demonstrates its value by facilitating the generation of new findings and insights by combining importance and performance dimensions in the analysis of PLS-SEM in real-world scenarios. 1. The IPMA not only evaluates path coefficients, but also considers the average values of latent variables and their indicators to analyze the performance aspect of a model (Teeluckdharry et al., 2022; Yapp & Yeap, 2023).

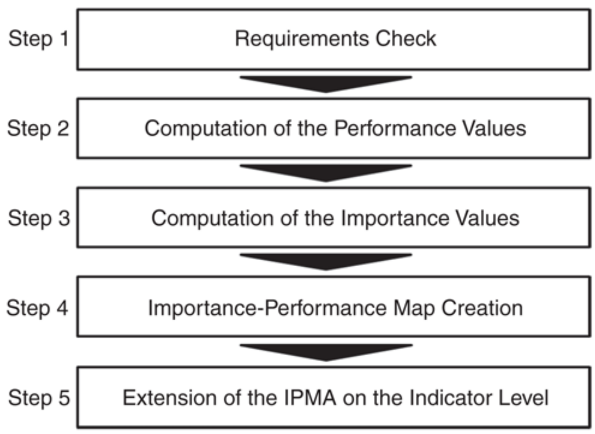

Figure 2. Steps of IPMA Analysis (Ringle & Sarstedt, 2016)

3. Findings and Discussion

The findings of the data analysis will be covered in this section. These findings are then applied in discussions to address the issues raised by this study. As shown in Table 1, only 101 of the 200 responses that were successfully obtained were favorable sufficiently to be examined further.

Table 1. Characteristics of Respondents' demographic

	Variable	Frequency	%
Gender	Female	67	66,34%
	Male	34	33,66%
Age (years)	<20	3	2,97%
	20-25	98	97,03%
Education	Diploma	13	12,87%
	Bachelor	88	87,13%
Semester	6	58	57,43%
	8	43	42,57%
Experience Using AI (years)	< 1	70	69,31%
	1-3	29	28,71%
	> 3	2	1,98%

Measurement model

The measurement model outlined in Table 2 comprises seven latent variables. It assesses the validity and reliability of the constructs in this study, encompassing convergent and discriminant validity (J. F. Hair, Risher, Sarstedt, & Ringle, 2019) . Each latent variable is measured by multiple indicators with varying loadings, all above 0.708, indicating strong individual item reliability. The Composite Reliability (CR) values for all constructs exceed the threshold of 0.7, ensuring internal consistency, and the Average Variance Extracted (AVE) values are all above 0.5, confirming convergent validity (J. Hair & Alamer, 2022). This suggests that the measurement model is robust and the indicators reliably measure their respective constructs (see Table 2).

Table 2. Measurement Model

Latent variable	Indicator	Loadings	Composite Reliability	AVE
System quality			0.863	0.612
	SQ_1	0.743		
	SQ_2	0.759		
	SQ_3	0.789		
	SQ_4	0.834		

Latent variable	Indicator	Loadings	Composite Reliability	AVE
Information quality			0.854	0.746
	IQ_1	0.881		
	IQ_2	0.846		
Service quality			0.826	0.614
	SvQ_1	0.801		
	SvQ_2	0.747		
	SvQ_3	0.800		
Perceived ease of use			0.847	0.649
	PEU_1	0.841		
	PEU_2	0.738		
	PEU_3	0.833		
Perceived usefulness			0.910	0.771
	PUS_1	0.919		
	PUS_2	0.896		
	PUS_3	0.816		
Attitude			0.833	0.556
	ATT_1	0.742		
	ATT_2	0.745		
	ATT_3	0.773		
	ATT_4	0.721		
Continuance Intention			0.916	0.784
	INT_1	0.903		
	INT_2	0.890		
	INT_3	0.863		

Table 3 displays the Heterotrait-Monotrait Ratio (HTMT) values for the variables in the model: System Quality, Information Quality, Service Quality, Perceived Ease of Use, Perceived Usefulness, Attitude, and Continuance Intention. The HTMT values for all constructs are less than 0.90, demonstrating discriminant validity among them (Hair Jr et al., 2021). This means that each concept is distinct from the others, which supports the overall validity of the measurement model (see Table 3).

Table 3. HTMT

	1	2	3	4	5	6
1. System Quality						
2. Information quality	0.713					
3. Service Quality	0.578	0.671				
4. Perceived ease of use	0.715	0.633	0.608			
5. Perceived usefulness	0.647	0.727	0.633	0.628		
6. Attitude	0.473	0.545	0.725	0.475	0.581	
7. Continuance Intention	0.452	0.462	0.528	0.538	0.643	0.528

Structure model

Prior to conducting structural relationship analysis (see Table 4), it is essential to assess collinearity in order to guarantee impartial regression results. This can be achieved by calculating the variance inflation factor (VIF), with a recommended threshold of less than 3 for the VIF value (J. Hair & Alamer, 2022). Given that the VIF value fell below the designated threshold (1.000–1.489), no issues of collinearity were identified in this investigation (refer to Table 4). Additionally, the structural model will be assessed based on the coefficient of determination (R2), effect size (f2), cross-validated redundancy (Q2), and the path coefficient (J. F. Hair et al., 2019). Regarding the value of R2, attitude predicted continuance intention (17.7%). All the application quality constructs predicted perceived ease of use (37.6%) and perceived usefulness (41.9%). Perceived ease of use and perceived usefulness predicted attitude (24.2%). Then, when assessing Q2, if the Q2 value is significant more than zero, the exogenous construct exhibits predictive association with the intrinsic construct (J. Hair & Alamer, 2022). The obtained Q2 values ranged from 0.111 to 0.307, indicating that the endogenous constructs have better predictive power than the intrinsic constructs. Effect size (f2) is one of the support criteria to determine whether an independent construct has a strong influence on a dependent construct.

Table 4. Hypothesis testing result

Hypotheses	β	T value	VIF	P Values	Supported
H1	0.372	3.879	1.459	0.000	Yes
H2	0.293	2.085	1.459	0.019	Yes
H3	0.149	1.519	1.489	0.064	No
H4	0.293	2.605	1.489	0.005	Yes
H5	0.249	2.667	1.351	0.004	Yes
H6	0.235	2.624	1.351	0.004	Yes
H7	0.196	1.752	1.356	0.040	Yes
H8	0.378	4.257	1.356	0.000	Yes
H9	0.431	6.023	1.000	0.000	Yes

Subsequently, evaluate path coefficients using bootstrapping and 10,000 subsamples to ensure that t-values are greater than 1.96 with 95% confidence. The eight hypotheses demonstrated statistical significance with a p-value of less than 0.05 and a t-value greater than 1.96. Conversely, hypothesis H3 was not supported. Furthermore, the results indicate that system quality has a significant positive impact on perceived ease of use (β = 0.372) and perceived usefulness (β = 0.293), providing support for hypotheses H1 and H2. Subsequently, the quality of information has a notably positive influence on perceived usefulness (β = 0.293), providing support for H4. Additionally, service quality was determined to have a significant effect on perceived ease of use (β = 0.249) and perceived usefulness (β = 0.235), thereby supporting H5 and H6. Moreover, perceived ease of use (β = 0.196) and perceived usefulness (β = 0.378) positively impact attitude, supporting H7 and H8. Finally, attitude influences continuance intention (β = 0.431), providing support for H9.

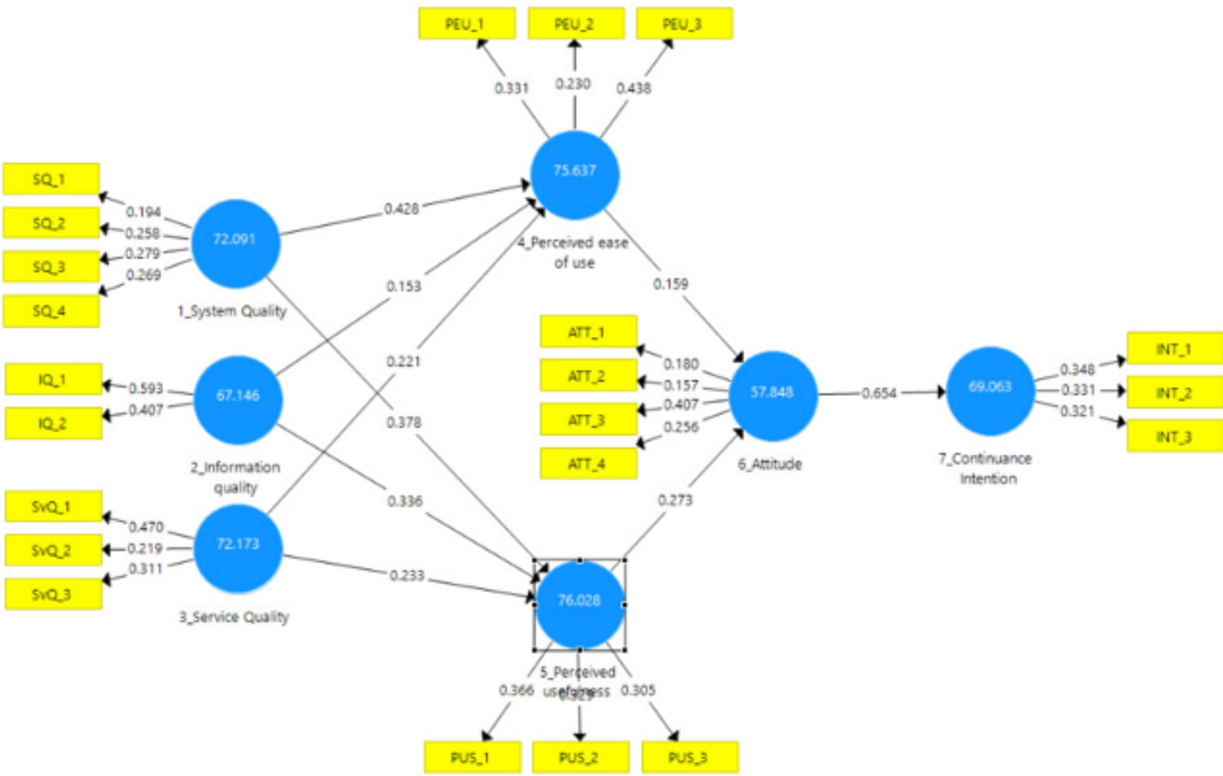

Figure 2. The summary of model

IPMA

IPMA was employed to assess constructs of significant importance and performance at a moderate to subpar level (Yapp & Yeap, 2023). Table 5 displays the significance and effectiveness scores for the key elements of attitude and intention to continue. In the target construct of continuance intention, attitude has the highest importance value (0.431) and performance is below average. This indicates that attitude is the most important construct in increasing continuance intention. In the target construct of attitude, the highest importance is in the perceived usefulness construct (0.378) with an average performance value. This shows the importance of perceived usefulness in improving attitude. However, other constructs, namely system quality (0.184), information quality (0.140), service quality (0.138), and perceived ease of use (0.196) also have equal importance values, which shows that these constructs also have a level of importance in influencing attitude.

Table 5. IPMA for Attitude and Continuance Intention

Constructs	Attitude		Continuance Intention	
	Importance	Performance	Importance	Performance
System Quality	0.184	72.091	0.079	72.091
Information quality	0.140	67.146	0.060	67.146
Service Quality	0.138	72.173	0.059	72.173
Perceived ease of use	0.196	75.637	0.085	75.637
Perceived usefulness	0.378	76.028	0.163	76.028
Attitude	-	-	0.431	57.848

The objective of this research is to investigate factors that motivate students to continue utilizing AI in marketing research. The finding indicates that attitude plays a pivotal role in increasing the willingness to persist in using AI. Attitude is the most important factor in the target construct of continuance intention (shown in Table 5). In line with previous studies, positives attitudes toward AI significantly enable the intention to continue usage (Ashfaq et al., 2020; Sohn & Kwon, 2020). This specifies that the more someone favors the use of AI, the higher their potential intention to keep using it. In addition, within the attitude construct, perceived usefulness holds the highest significance and has an average performance value, underscoring its role in shaping attitude. Perceived utility pertains to the user's conviction that technology enhances their overall experiences (Yapp & Yeap, 2023) . The finding implies that perceived usefulness boosts attitude, the greater the assistance users receive from AI, the more positively they will evaluate it (Jo, 2023; Kasuma et al., 2020). Within the framework of marketing research, AI can be utilized to analyze large and complex customer data quickly and accurately. For example, in the data collection process, artificial intelligence (AI) can be a very useful instrument. AI can help identify relevant data sources, collect data automatically, and clean and format the data so it is ready for further analysis (Friedrich et al., 2022). With advanced analytical capabilities, AI can identify patterns, trends and important insights from the data (Zhang & Song, 2022). This information can be used to understand customer behavior, better segment markets, predict purchasing trends, and optimize marketing strategies.

Nonetheless, other constructs, including system quality, information quality, service quality, and perceived ease of use, also have considerable importance, indicating their influence on attitude as well. The system quality, information quality, service quality, and perceived ease of use have comparable importance values, which shows that these variables also play a role in shaping attitude (shown in Table 5). Previous studies have shown that users' perceptions of system quality play an important role in determining their attitudes toward and acceptance of technology (Al-Debei, Akroush, & Ashouri, 2015; Hanjaya et al., 2019). Users will like AI if the system operates smoothly and efficiently (Cai, Lin, & Yu, 2023). The use of AI in marketing research may also pose risks to consumers, such as privacy violations, identity theft, or exposure to harmful content (Verma et al, 2021). For example, AI-powered chatbots could inadvertently reveal sensitive personal information or transmit inappropriate content to consumers, which could harm reputations and give rise to legal liability. Companies must guarantee that their AI systems are developed and executed securely and ethically to tackle these security issues. (Verma et al., 2021). Thorough testing and assessment are carried out to detect and address possible technical issues, along with the implementation of suitable security measures to safeguard consumer privacy and minimize potential risks.

In addition, AI can help collect data from various sources, analyze the data thoroughly, and provide accurate and detailed information that can be used to make informed decisions (Kieslich, 2022). Consistent with prior research, the results of this study also prove that enhanced AI information quality boosts users' confidence in the system and empowers them to make well-informed decisions utilizing the presented information (Ghasemaghaei & Hassanein, 2019; Priyadarshini, Sreejesh, & Anusree, 2017). In marketing research, users can ask AI systems to summarize research data, generate information, provide recommendations to make decisions based on data. AI systems must be transparent and explainable (Salleh, 2023). It is essential for the AI user to have an understanding of how AI algorithms arrive at decisions and the utilization of their data in informing those decisions (Kieslich, 2022; Salleh, 2023). AI Chatbot services which are generally used in marketing research are in the form of information, so that if the AI Chatbot provides invalid information indicates that the system is not reliable and detrimental to consumers. In Indonesia in the context of consumer protection, Article 8 paragraph (2) of the Consumer Protection Law states that business actors are prohibited to trade AI Chatbot services that the system does not reliable (Putra, 2023). Moreover, the quality of service encompasses the aid and support provided to users before, during, and after their engagement with a technology or system, further influencing users' favorability towards AI (Azzahra & Kusumawati, 2023). Finally, AI equipped with high-quality system, information and service is believed to enhance the perceived ease of use, thereby increasing user preference for AI (Kasuma et al., 2020; Machdar, 2016).

The results of this research are expected to provide valuable perspectives on efficiently handling the benefits and challenges, such as ethical issues, linked to the incorporation of AI, especially in the field of marketing research.

4. Conclusions and Suggestions

This study examines factors influence students' intentions to continue using AI for marketing research by applying the Technology Acceptance Model (TAM). Perceived usefulness is highlighted as the most substantial factor within attitude, indicating that users believe their experiences are enhanced by AI. Additional elements like system quality, data quality, customer service quality, and perceived simplicity of use can impact individuals' attitudes and acceptance of AI. The findings suggest that smooth system operation, enhanced information quality, and high-quality systems, service and information contribute to users' positive perceptions and preferences for AI.

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