Assessing the Adoption Intention of Computational Intelligence Technologies in the E-Commerce Industry

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ABSTRACT

Rapid advances in information technology have brought significant changes to the role of e-commerce, as well as changing the way electronic customers engage with interactive marketing, in connection with the presence of computational intelligence. This study aims to analyze the influence of CI service quality, CI information quality, social influence on e-customer perceived value, intention to adopt CI, and use behavior. The research approach used is quantitative, with SEM-PLS data processing using SMARTPLS software. The results of the study revealed that CI Service quality and CI information quality have a significant influence on E-Customer Perceived Value. Social influence and E-customer perceived value have a significant influence on intention to adopt AI, intention to adopt AI has a significant influence on use behavior and is able to mediate the relationship between social influence and use behavior. However, E-Customer Perceived Value is not able to mediate the relationship between CI Service quality and CI information quality on Use behavior.

Keywords: CI service quality, CI information quality, social influence, e-customer perceived value, intention to adopt CI.

INTRODUCTION

E-commerce has undergone significant transformation in the landscape of business and trade. The presence of e-commerce fosters growth, exploration of new opportunities, and management of organizational changes to remain competitive (Xin et al., 2023). Among Southeast Asian countries, Indonesia dominates the e-commerce market, reaching a transaction value of USD 82 billion. The main driver of this growth is the significant increase in the number of electronic commerce users in Indonesia, which is projected to rise to 99 million users by 2029 (Statista.com, 2024). Globally, this evolution has made it easier for customers to purchase products anytime and has transformed fulfillment into a key and technology-intensive sector (Tsai & Tang, 2023). As a result, the rapid progress of information technology has brought about significant changes in the role of e-commerce, simultaneously reshaping how electronic customers engage in interactive marketing (IM) (Gao & Liu, 2022).

The concept of IM refers to a marketing strategy that emphasizes two-way value exchange and reciprocal influence between businesses and customers through active connections, engagement, and interaction (Gligor & Bozkurt, 2021). Therefore, it is crucial to examine electronic customers' willingness to adopt computational intelligence (CI) within the framework of IM (Behera et al., 2024).

CI is characterized as a computational approach that enables information systems to adapt to environmental changes and acquire new capabilities by generating rational outcomes. In this context, CI surpasses traditional IT in terms of its recommendation and prediction abilities (Jiang et al., 2022). Within IM, CI can respond to customer inquiries about personalized product suggestions (Gao & Liu, 2022). Similarly, this applies to the use of CI in e-commerce. Hence, CI is considered the core technology of IM, prompting further exploration of the quality of CI systems and the information they produce (Behera et al., 2024).

The quality of a CI system refers to the ease of use, reliability, functionality, and flexibility of the system in supporting IM activities. Meanwhile, CI information quality encompasses the relevance and accuracy of information provided by CI in decision-making within IM. Previous studies have examined system and information quality in various contexts to promote sustainability (Rana et al., 2023; Shiau & Huang, 2023).

However, those studies have not specifically addressed the effect of CI system quality or CI information quality, nor have they investigated these factors within the IM context (Gao & Liu, 2022).

Furthermore, IM is driven by customer perceptions, needs, and behaviors (Gligor & Bozkurt, 2021). The relationship between CI and customers has been explored in the literature, showing that CI principles can be applied to profile, categorize, and personalize offerings for specific customer segments (Guerra-Montenegro et al., 2021). Nevertheless, no prior research has examined how CI system quality and information quality influence electronic customer perceived value, defined as the overall evaluation of the benefits obtained from using an information system while considering the associated costs and trade-offs (Sharma & Fathimah, 2024). Therefore, electronic customer perceived value represents an essential aspect of IM.

Previous research on intention to adopt CI and use behavior has generally focused on factors such as user reviews (Jiang et al., 2022), discounts and special offers (Senali et al., 2022), and system quality, variety, and capabilities (Song et al., 2022), all of which can encourage adoption of certain applications. In this regard, the researcher aims to strengthen prior studies by including additional variables alongside system and information quality—namely social influence and e-customer perceived value, both of which may affect use behavior. Thus, this study, titled "Analysis of Computational Intelligence Adoption Intention in the E-Commerce Business," seeks to analyze the application of CI in e-commerce businesses conducted by the community in Batam City.

THEORETICAL FRAMEWORK AND LITERATURE REVIEW

Artificial Intelligence

Artificial Intelligence (AI) has profoundly influenced many fundamental aspects of modern life, shaping how people interact, communicate, and conduct business (Song et al., 2022). Digital technology encompasses various systems, tools, and devices that leverage computing and the internet to process, store, and transmit data. This process includes multiple efforts, ranging from the use of smartphones and tablets to cloud computing and big data analytics (Stahl, 2021). As part of digital technology, AI refers to the simulation of human intelligence implemented in machines programmed to learn and reason (Lyu & Liu, 2021). The integration of AI into digital technologies has driven substantial progress through machine learning algorithms used to analyze large datasets, identify patterns, predict outcomes, and automate tasks that previously required human intervention (Bag et al., 2021).

For example, in the world of business and commerce, AI can improve operational efficiency through the use of chatbots to provide better customer service, the application of predictive analytics for inventory management, and personalized marketing strategies based on consumer preferences. Furthermore, digital technology and AI are also transforming the financial industry, where algorithms analyze market trends in real-time, enabling faster investment decisions and risk assessments (Gao & Liu, 2022).

Computational Intelligence

Computational Intelligence, or CI, is characterized as a computation-based approach that enables information systems to adapt to environmental changes and acquire new capabilities, while providing a rationale for their use. In this context, CI outperforms traditional IT in terms of recommendation and prediction capabilities (Jiang et al., 2022). In the context of IM, IT is capable of responding to customer inquiries regarding personalized product suggestions (Gao & Liu, 2022). The same is true for the application of CI in e-commerce. Thus, CI can be considered a core IM technology, encouraging further exploration of the quality of CI systems and the information they generate (Behera et al., 2024).

Unified Theory of Acceptance and Use of Technology (UTAUT)

UTAUT is characterized as a model developed in an effort to understand the factors that can influence the demand for and utilization of technology (Blut et al., 2022). This model integrates eight different theories on technology acceptance, such as TAM (Technology Acceptance Model), TRA (Theory of Reasoned Action), and DOI (Diffusion of Innovation), to provide a comprehensive picture related to the technology adoption process (Aytekin et al., 2022). In UTAUT, there are four main factors that can influence technology use: Performance Expectancy (expectations regarding technology performance), Effort Expectancy (ease of use of technology), Social

Influence (social influence or pressure from the social environment to use technology), and Facilitating Conditions (supportive conditions, such as infrastructure or necessary skills) (Ayaz & Yanartas, 2020). In addition, this model also considers four moderating variables that influence the relationship between these factors and technology use intentions and behaviors, namely age, gender, experience, and voluntary use of technology (Chopdar, 2022). In this context, UTAUT theory has been widely used in research to predict and explain technology adoption in various contexts and sectors (Xue et al., 2024).

Definition of Dependent Variable

CI use behavior refers to the extent to which customers or active users integrate and utilize computational intelligence (CI) technology in their daily activities, particularly in the context of e-commerce (Behera et al., 2024; Jiang et al., 2022). It can also include how frequently and in what contexts they use CI-driven systems, such as product recommendation algorithms, chatbots, predictive analytics, and automated personalized shopping experiences (Gao & Liu, 2022; Song et al., 2022; Tsai & Tang, 2023).

The Effect of CI Service Quality on E-Customer Perceived Value

CI service quality refers to the extent to which CI can deliver a good, reliable, and trustworthy system to provide convenience to e-customers (Behera et al., 2024). Good CI system quality, which includes ease of use, reliability, functionality, and flexibility, can enhance the user experience and simplify their interaction with the e-commerce platform (Li & Shang, 2021). If a CI system is designed with an easy-to-understand interface and delivers consistent and accurate results, customers will feel more satisfied and confident in using the technology (Samudro et al., 2020; Uzir et al., 2021). This can also contribute to increased e-customer perceived value, where customers perceive that the benefits they gain from using the CI system outweigh the costs and effort they incur (Naqvi et al., 2021).

H1: CI Service Quality has a significant effect on E-Customer Perceived Value

The Effect of CI Information Quality on E-Customer Perceived Value

Relevant, accurate, and timely information from CI systems can increase customer trust in e-commerce platforms and help them make better purchasing decisions (Patma et al., 2021; Li & Shang, 2020). When CI systems provide product recommendations that align with individual preferences and provide easy-to-understand and useful information, customers perceive greater benefits from using the technology (Behera et al., 2024). This contributes to increased e-customer perceived value, where customers assess that the benefits derived from the information provided outweigh the costs or effort incurred (Putri & Pujani, 2019; Maria et al., 2021).

H2: CI Information Quality has a significant effect on E-Customer Perceived Value

The Influence of Social Influence on Intention to Adopt CI

In the context of e-commerce, social influence refers to the extent to which individuals are influenced by others, such as friends, family, colleagues, or influencers, in their decision to use new technologies like CI (Faqih et al., 2020; Li et al., 2022). In many cases, recommendations or positive opinions from those close to them can increase an individual's confidence in adopting the technology (Guetz & Bidmon, 2022). If an individual sees that others, especially those they perceive as influential or authoritative, have successfully used CI and benefited from it, they are more likely to be interested in trying and adopting the same technology (Nguyen, 2021). In the context of e-commerce, this social influence can take the form of customer reviews, testimonials, or even endorsements from popular figures who use and recommend CI-based systems (GC et al., 2024).

H3: Social Influence has a significant effect on Intention to Adopt CI

The Influence of E-Commerce Perceived Value on Use Behavior

When customers perceive significant value from their online shopping experience, whether in terms of efficiency, personalization, or the perceived benefits of using technologies such as computational intelligence (CI), they are more likely to use the e-commerce platform (Behera et al., 2024; Rahi et al., 2020). Perceived value includes aspects such as convenience, time savings, product relevance, and accurate recommendations, all of which can increase customer satisfaction (Rahi & Ishaq, 2020; Rahardja et al., 2021). If customers perceive that the benefits they receive outweigh the costs, they will be more motivated to continue using the service or system (Tumewah & Kurniawan, 2020).

H5: E-Customer Perceived Value has a significant effect on Use Behavior

The Influence of Intention to Adopt CI on Use Behavior

Essentially, when customers have a strong intention to adopt CI, they tend to use the technology more frequently in their shopping activities (Moorthy et al., 2019; Lin et al., 2020). Adoption intention reflects customers' belief and desire to try and integrate new technologies they perceive as enhancing their experiences, such as more accurate product recommendations, personalized services, and efficient decision-making (Radhamani et al., 2021). When customers already have a positive intention to use CI, they are more likely to interact with systems driven by this technology, whether through using applications, shopping, or utilizing features provided by e-commerce platforms (Bajunaeid et al., 2023; Purwanto & Loisa, 2020).

H6: Intention to Adopt CI has a significant effect on Use Behavior

The Mediation of E-Customer Perceived Value in the Influence of Information Quality on Use Behavior

When a CI system provides product information that aligns with actual factual situations and individual preferences, and provides information that is easy to understand and useful, customers will perceive greater benefits from using the technology (Behera et al., 2024; Maria et al., 2020). When customers perceive significant value from the online shopping experience, whether in terms of efficiency, personalization, or the perceived benefits of using technologies such as computational intelligence (CI), they are more likely to use the e-commerce platform (Rahi et al., 2020). In this context, perceived value includes aspects such as convenience, time savings, product relevance, and accurate recommendations, all of which can increase customer intention to use the service (Tumewah & Kurniawan, 2020; Rahardja et al., 2021).

H7: E-Customer Perceived Value mediate the influence of Information Quality on Use Behavior

The Mediation of E-Customer Perceived Value in the Influence of Service Quality on Use Behavior

Good CI system quality, including ease of use, reliability, functionality, and flexibility, can enhance the user experience and simplify their interaction with the e-commerce platform (Li & Shang, 2021). If the CI system is designed with an easy-to-understand interface and delivers consistent and accurate results, customers will feel more satisfied and confident in using the technology (Samudro et al., 2020; Uzir et al., 2021). When customers perceive significant value from the online shopping experience, this can lead to a tendency to use the e-commerce platform more frequently (Rahi et al., 2020). In this context, perceived value can be an important antecedent shaping usage behavior among customers (Tumewah & Kurniawan, 2020; Rahardja et al., 2021).

H8: E-Customer Perceived Value mediate the effect of System Quality on Use Behavior

Mediating Intention to Adopt CI in the Effect of Social Influence on Use Behavior

If someone sees that others, especially those they perceive as influential or authoritative, have successfully used CI and benefited from it, they are more likely to be interested in trying and adopting the same technology (GC et al., 2024; Nguyen, 2021). When customers have a strong intention to adopt CI, they are more likely to use the technology in their shopping activities (Moorthy et al., 2019; Lin et al., 2020). Furthermore, customers who already have positive intentions towards using CI are more likely to interact with systems driven by this technology, whether through using applications, shopping, or utilizing features provided by e-commerce platforms (Bajunaeid et al., 2023; Purwanto & Loisa, 2020).

H9: Intention to Adopt CI mediates the effect of Social Influence on Use Behavior

A research model is a reference and basic framework that represents the causal relationship between research variables, including independent, dependent, and mediating variables. The context of this research is to examine

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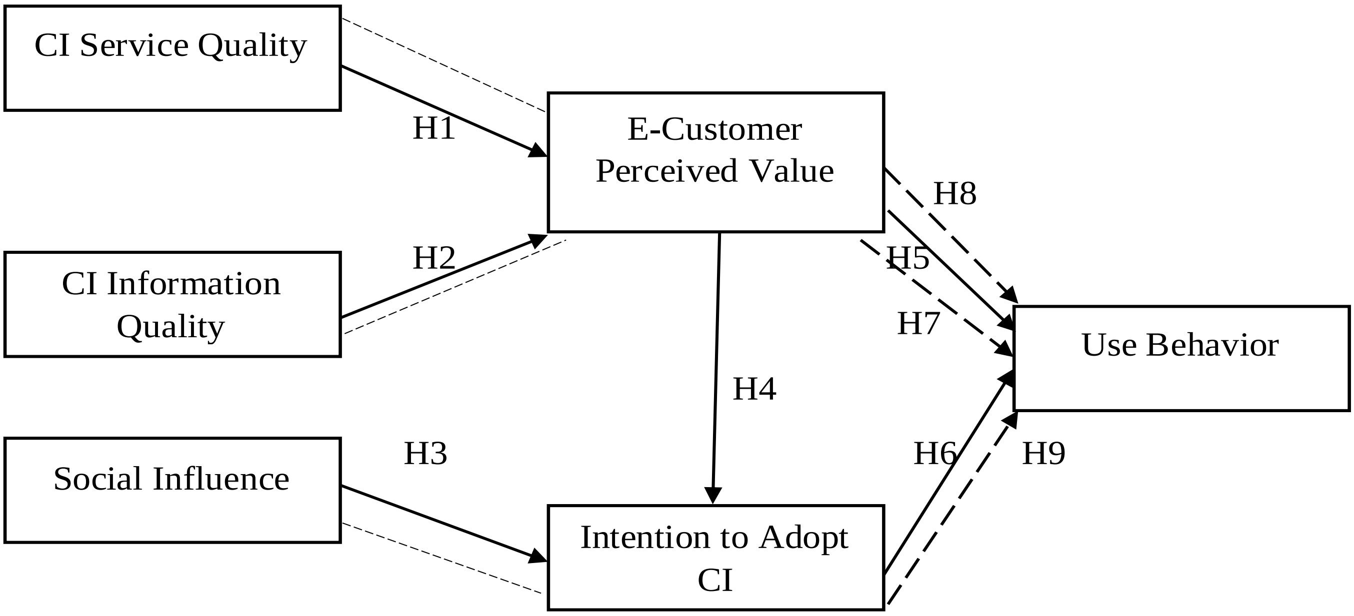
the influence of CI service quality, CI information quality, and social influence on e-customer perceived value, intention to adopt CI, and usage behavior. This is illustrated in Figure 2.1 below.



Research Framework

RESEARCH METHOD

This research uses a quantitative approach utilizing Causal-Comparative Research techniques, aimed at identifying the causal relationship between independent and dependent variables, along with mediating variables (Sugiyono, 2021). The population in this study was e-commerce users who had experienced the usefulness of the computational intelligence feature. This study was conducted using a questionnaire as a medium for data collection, obtained from a survey of respondents. Given that the population size was unknown, the sample size was taken at a ratio of 1:10, with each question item representing 10 respondents.

This study included 18 questions, resulting in a minimum sample size of 180. To avoid insufficient data collection, the target sample size was 303. The sampling approach chosen was non-probability sampling with a purposive sampling method, which involves selecting a sample based on specific considerations and criteria observed by the researcher: e-commerce users with computational intelligence features, residents of Batam, and aged 18-50. The sample was obtained by distributing questionnaires to respondents who met the relevant requirements or criteria.

In this study, there are 3 types of variables, namely independent variables, mediating variables, and dependent variables where CI service quality, CI information quality, social influence as independent variables, e-customer perceived value and intention to adopt CI as mediating variables against use behavior which is the dependent variable. This research was tested using the SEM-PLS (Structural Equation Modeling) program, also known as a structural equation model. This statistical technique is used to test statistical models in the form of causal correlations. This model is capable of viewing, observing, and accommodating structural models in their entirety. Meanwhile, PLS, as a regression-based method, can be used in the model creation process, assuming that the research data is distribution-free, meaning that the research data does not refer to the magnitude of its distribution.

Tabel 1. Daftar Item Kuesioner

No.	Items	Source
CI Service Quality		
CISQ1	*I think that the computational intelligence system is easy to use.*	
CISQ 2	*I think that the computational intelligence system is user-friendly*	
CISQ 3	*I think using the computational intelligence system is comfortable*	

CI Information Quality		
CIIQ1	*I think the information provided by the computational intelligence system is reliable.*	
CIIQ2	*I think the information provided by the computational intelligence system is accurate.*	
CIIQ3	*I think the information provided by the computational intelligence system is up-to-date.*	
Source Influence		
	People who are important to me think I should use computational intelligence	
	People who influence my behavior think I should use computational intelligence	
	People whose opinions I value prefer I should use computational intelligence.	
e-Customer Perceived Value		
	I would enjoy the computational intelligence-recommended products.	
	I think the computational intelligence-recommended products feel acceptable.	
	I think computational intelligence-recommended products are reasonably priced	
Intention to Adopt CI		
	I intend to adopt computational intelligence in the future.	
	I will continue to use computational intelligence in the future.	
	I will regularly use computational intelligence in the future.	
Use Behavior		
	I want to use all computation intelligence features	
	I will use computation intelligence if it is available	
	I will recommend using computation intelligence in the future	

RESULTS AND DISCUSSION

Table 1. Respondent Demographics

Criteria	Category	Frekuensi	Persentase
Jenis Kelamin	Pria	119	39.3%
	Wanita	184	60.7%
Total		303	100.0%
Age	18-25 tahun	151	49.8%
	26-30 tahun	100	33%
	31-40 tahun	45	14.9%
	41-50 tahun	7	2.3%
Total		303	100%
Education	Highschool	128	42.2%
	Diploma	51	16.8%
	S1	108	35.6%
	S2	15	5%
Total		303	100.0%

Sumber: Data primer yang diolah peneliti, 2025

Respondent demographic data includes gender, age, highest education, and length of service, as presented in table 3. Data obtained from 303 respondents stated that based on gender, the majority of respondents were female with a percentage of 60.7%, while the other 39.3% were male. According to age, there were 49.8% of respondents in the age range of 18-25 years, 33.0% aged 26-30 years, 14.9% aged 31-40 years, and the remaining 2.3% aged 41-50 years. For educational level, the largest group of respondents (42.2%) had a high school education, 35.6% had a bachelor's degree, 16.8% had a diploma, and 5.0% had a master's degree.

Table 2. Outer Model Test

Contruct	Item	*Convergent Validity (Outer Loading)*	*Discriminant Validity (AVE)*	*Composite Reliability*	*Cronbach Alpha*	*R Square*
CI Information Quality	CIIQ1	0.824	0.562	0.793	0.609	
	CIIQ2	0.698				
	CIIQ3	0.720				
CI Service Quality	CISQ1	0.708	0.550	0.786	0.592	
	CISQ2	0.744				
	CISQ3	0.772				
e-Customer Perceived Value	ECPV1	0.809	0.598	0.817	0.663	0.473
	ECPV2	0.746				
	ECPV3	0.764				
Intention to Adopt CI	IACI1	0.765	0.559	0.791	0.605	0.469
	IACI2	0.704				
	IACI3	0.772				
Socal Influence	SI1	0.841	0.678	0.863	0.763	
	SI2	0.817				
	SI3	0.812				
Use Behavior	UB1	0.776				
	UB2	0.686	0.511	0.758	0.520	0.457
	UB3	0.679				

Source: Processed Primary Data (2025).

This approach aims to evaluate the contribution of specific factors to the indicators of related variables. To ensure the validity of questionnaire items, researchers refer to the results of the outer load values, with the criterion that a question is considered valid if its outer load value is greater than 0.6 (Hair Jr et al., 2021). According to the results presented in Table 4, it can be concluded that all questions related to the research variables have an outer load greater than 0.6, indicating that all items have passed convergent validity. Researchers also conducted an AVE test, which stipulates that a questionnaire item is valid if it has an AVE value of > 0.5. Based on this provision, it can be said that all variables have an AVE value of > 0.5, meaning they are valid.

Reliability testing was conducted to determine the consistency of the measuring instrument. This study used the theory of Hair Jr. et al. (2021), which states that an instrument can be considered reliable if the Cronbach Alpha value is ≥ 0.6, and Composite Reliability ≥ 0.7. In this case, it can be stated that according to Cronbach Alpha, the CI Service quality and Use behavior indicators are not yet reliable because they have values below 0.520. However, in terms of composite reliability, all meet the requirements above 0.7, meaning they are reliable.

Based on the results above, it can be interpreted that the adjusted R-Square E-Customer perceived value is 0.470, meaning that the independent variable is able to explain the E-Customer perceived value variable by 47.0%. Then, the adjusted R-Square Intention to adopt CI value is 0.465, meaning that the independent variable is able to explain the Intention to adopt CI variable by 46.5%. In addition, the adjusted R-Square use behavior value is 0.448, meaning that the independent variable is able to explain the use behavior variable by 44.8%.

Table 3. T-test

XY	T-statistic	p-value	Conclusion	Information
CI service quality –> E customer perceived value	5.867	0,000	Significant Positive	H1 Accepted
CI Information quality -> E- Customer perceived value	7.350	0,000	Significant Positive	H2 Accepted

Social influence -> Intention to adopt CI	3.395	0.001	Significant Positive	H3 Accepted
E-Customer Perceived Value -> Intention to adopt CI	8.690	0,000	Significant Positive	H4 Accepted
E-Customer Perceived Value -> Use behavior	1.206	0.336	Significant Positive	H5 Accepted
Intention to adopt CI -> Use behavior	5.056	0,000	Significant Positive	H6 Accepted
Information Quality -> E-Customer Perceived Value -> Use Behavior	1.138	0.255	Insignificant	H7 Rejected
Service Quality -> E-Customer Perceived Value -> Use Behavior	1.195	0.232	Insignificant	H8 Rejected
Information Quality -> E-Customer Perceived Value -> Social Influence -> Intention to adopt CI -> Use behavior	2.737	0.006	Significant Positive	H9 Accepted

Source: Processed Primary Data (2025).

DISCUSSION

The results of the study indicate that CI Service Quality has a significant influence on E-Customer Perceived Value. This is evidenced by the calculated T value of 5.867 and p value of 0.000. This supports the results of research conducted by (Samudro et al., 2020; Uzir et al., 2021), which stated that if the CI system is designed with an easy-to-understand interface and provides consistent and accurate results, customers will feel more satisfied and confident in using the technology. This can also contribute to increasing e-customer perceived value, where customers assess that the benefits they obtain from using the CI system exceed the costs and efforts they incur (Naqvi et al., 2021). Thus, H1 is accepted.

The results of the study indicate that CI Information Quality has a significant influence on E-Customer Perceived Value. This is evidenced by the calculated T value of 7.350 and p value of 0.000. This is in line with research (Behera et al., 2024) which states that when the CI system provides product recommendations that match individual preferences, as well as providing easy-to-understand and useful information, customers will feel that they get greater benefits from using the technology. This contributes to an increase in e-customer perceived value, where customers assess that the benefits obtained from the information provided are higher than the costs or effort incurred (Putri & Pujani, 2019; Maria et al., 2021). Thus, H2 is accepted.

The results of the study indicate that social influence has a significant influence on the intention to adopt CI. This is evidenced by the calculated T value of 3.395 and a p value of 0.001. These results support the findings of Guetz & Bidmon, 2022, which state that recommendations or positive opinions from those closest to them can increase an individual's confidence in adopting the technology. If someone sees that others, especially those they perceive as influential or authoritative, have successfully used CI and benefited from it, they are more likely to be interested in trying and adopting the same technology (Nguyen, 2021). Thus, H3 is accepted.

The results of the study indicate that e-customer perceived value has a significant influence on the intention to adopt CI. This is evidenced by the calculated T value of 8.690 and p value of 0.000. The results of this study support the findings of (Sreelakshmi & Prathap, 2023; Uzir, 2021) which state that if customers perceive that CI technology provides a more personalized, relevant, and efficient shopping experience, as well as providing additional benefits such as accurate recommendations and time savings, then they will be more likely to adopt the technology. Conversely, if customers perceive that the use of CI does not provide clear added value or leads to a poor experience, they will be hesitant to adopt it (Sartono et al., 2024). Thus, H4 is accepted.

The results of the study indicate that e-customer perceived value does not significantly influence usage behavior. This is evidenced by the calculated T value of 1.206 and p value of 0.336. The results of this study reject the findings of (Rahi & Ishaq, 2020; Rahardja et al., 2021) which state that perceived value includes aspects such as convenience, time savings, product relevance, and accurate recommendations, all of which can increase customer satisfaction. If customers perceive that they gain more benefits than the costs they incur, they will be more motivated to continue using the existing service or system (Tumewah & Kurniawan, 2020). Thus, H5 is rejected.

The results of the study indicate that intention to adopt CI has a significant influence on use behavior. This is evidenced by the calculated T value of 5.056 and a p value of 0.000. These results support the findings of (Radhamani et al., 2021) who stated that adoption intention reflects customers' beliefs and desires to try and integrate new technologies that they perceive can improve their experience, such as more accurate product recommendations, service personalization, and efficiency in decision-making. If customers already have a positive intention towards using CI, they are more likely to interact with systems driven by this technology, whether in the form of using applications, shopping, or utilizing features provided by e-commerce platforms (Bajunaeid et al., 2023; Purwanto & Loisa, 2020). Thus, H6 is accepted.

The results of the study indicate that E-customer perceived value is unable to mediate the effect of information quality on use behavior. This is evidenced by the calculated T value of 1.138 and p value of 0.255. The results of this study reject the findings of (Behera et al., 2024; Maria et al., 2020) which state that when the CI system provides product information that is in accordance with the actual factual situation and individual preferences, and provides information that is easy to understand and useful, customers will feel that they get greater benefits from using the technology (Behera et al., 2024; Maria et al., 2020), nor does it support the research conducted by (Rahi et al., 2020) which states that customers who feel that they get significant value from the online shopping experience, both in terms of efficiency, personalization, and perceived benefits from using technologies such as computational intelligence (CI), they tend to use the e-commerce platform more frequently. Thus, H7 is rejected.

The results of the study indicate that e-customer perceived value is unable to mediate the effect of service quality on use behavior. This is evidenced by the calculated T value of 1.195 and p value of 0.232. These results reject previous research findings that stated that if the CI system is designed with an easy-to-understand interface and provides consistent and accurate results, customers will feel more satisfied and confident in using the technology (Samudro et al., 2020; Uzir et al., 2021). When customers perceive that they gain significant value from the online shopping experience, it can create a tendency for customers to use the e-commerce platform more frequently (Rahi et al., 2020). Thus, H8 is rejected.

The results of the study indicate that Intention to adopt CI is able to mediate the influence of Social influence on Use behavior. This is proven by the calculated T value of 2.737 and p value of 0.006. The results of this study support the findings (GC et al., 2024; Nguyen, 2021) which state that if someone sees that others, especially those they consider to have influence or authority, have successfully used CI and benefited from it, then they are more likely to be interested in trying and adopting the same technology, and when customers have a strong intention to adopt CI, they tend to use the technology more often in their shopping activities (Moorthy et al., 2019; Lin et al., 2020). Thus, H9 is accepted.

CONCLUSION

This study examined the factors influencing the adoption and utilization of computational intelligence (CI) technologies in the e-commerce industry, focusing on users in Batam City. The findings reveal that CI service quality, CI information quality, and social influence significantly affect e-customer perceived value and intention to adopt CI, which subsequently influence use behavior. Among these variables, intention to adopt CI plays a crucial mediating role between social influence and use behavior, indicating that users’ behavioral engagement with CI systems is strongly driven by social encouragement and individual willingness to adopt the technology.

Conversely, the study found that e-customer perceived value does not significantly influence use behavior and fails to mediate the relationships between CI service quality or CI information quality and use behavior. This suggests that while users may recognize the benefits of CI systems, these perceptions alone do not guarantee continuous use unless accompanied by strong adoption intentions. The findings highlight the importance for e-commerce platforms to enhance service and information quality, while also leveraging social influence to strengthen user engagement and adoption intention.

Future research is recommended to incorporate moderating variables such as trust, perceived risk, user experience, and technological readiness, which may shape the strength of the relationships among CI-related constructs. Additionally, longitudinal or comparative studies across different e-commerce sectors and regions could provide broader validation of the model and capture potential contextual differences in CI adoption behavior. Further, employing mixed-method approaches, such as interviews or focus group discussions, could offer richer insights into users' motivations, emotional responses, and barriers to adopting computational intelligence in digital commerce environments.

REFERENCE

1. Ayaz, A., & Yanartaş, M. (2020). An analysis on the unified theory of acceptance and use of technology theory (UTAUT): Acceptance of electronic document management system (EDMS). *Computers in Human Behavior Reports*, *2*, 100032.
2. Aytekin, A., Özköse, H., & Ayaz, A. (2022). Unified theory of acceptance and use of technology (UTAUT) in mobile learning adoption: Systematic literature review and bibliometric analysis. *COLLNET Journal of Scientometrics and Information Management*, *16*(1), 75-116.
3. Bag, S., Srivastava, G., Bashir, M. M. A., Kumari, S., Giannakis, M., & Chowdhury, A. H. (2022). Journey of customers in this digital era: Understanding the role of artificial intelligence technologies in user engagement and conversion. *Benchmarking: An International Journal*, *29*(7), 2074-2098.
4. Behera, R. K., Bala, P. K., & Rana, N. P. (2024). Assessing the intention to adopt computational intelligence in interactive marketing. *Journal of Retailing and Consumer Services*, *78*, 103765.
5. Bajunaied, K., Hussin, N., & Kamarudin, S. (2023). Behavioral intention to adopt FinTech services: An extension of unified theory of acceptance and use of technology. *Journal of Open Innovation: Technology, Market, and Complexity*, *9*(1), 100010.
6. Blut, M., Chong, A. Y. L., Tsiga, Z., & Venkatesh, V. (2022, January). Meta-analysis of the unified theory of acceptance and use of technology (UTAUT): challenging its validity and charting a research agenda in the red ocean. Association for Information Systems.
7. Chopdar, P. K. (2022). Adoption of Covid-19 contact tracing app by extending UTAUT theory: Perceived disease threat as moderator. *Health Policy and Technology*, *11*(3), 100651.
8. Faqih, K. M. (2020). The influence OF perceived usefulness, social influence, internet self-efficacy and compatibility ON USERS'INTENTIONS to adopt e-learning: investigating the moderating effects OF culture. *IJAEDU-International E-Journal of Advances in Education*, *5*(15), 300-320.
9. Gao, Y., & Liu, H. (2022). Artificial intelligence-enabled personalization in interactive marketing: a customer journey perspective. Journal of Research in Interactive Marketing.
10. GC, S. B., Bhandari, P., Gurung, S. K., Srivastava, E., Ojha, D., & Dhungana, B. R. (2024). Examining the role of social influence, learning value and habit on students' intention to use ChatGPT: the moderating effect of information accuracy in the UTAUT2 model. *Cogent Education*, *11*(1), 2403287.
11. Gligor, D., & Bozkurt, S. (2021). The role of perceived social media agility in customer engagement. Journal of Research in Interactive Marketing, 15(1), 125-146.
12. Guerra-Montenegro, J., Sanchez-Medina, J., Lana, I., Sanchez-Rodriguez, D., Alonso-Gonzalez, I., & Del Ser, J. (2021). Computational Intelligence in the hospitality industry: A systematic literature review and a prospect of challenges. Applied Soft Computing, 102, 107082
13. Guetz, B., & Bidmon, S. (2022). The impact of social influence on the intention to use physician rating websites: moderated mediation analysis using a mixed methods approach. *Journal of Medical Internet Research*, *24*(11), e37505.
14. Hair Jr, J. F., Hult, G. T. M., Ringle, C. M., Sarstedt, M., Danks, N. P., & Ray, S. (2021). *Partial least squares structural equation modeling (PLS-SEM) using R: A workbook* (p. 197). Springer Nature.
15. Jiang, L., Zhou, W., Ren, Z., & Yang, Z. (2022). Make the apps stand out: discoverability and perceived value are vital for adoption. Journal of Research in Interactive Marketing, 16(4), 494-513
16. Jiang, Y., Wang, X., & Yuen, K. F. (2021). Augmented reality shopping application usage: The influence of attitude, value, and characteristics of innovation. Journal of Retailing and Consumer Services, 63, 102720.
17. Li, Y., & Shang, H. (2020). Service quality, perceived value, and citizens' continuous-use intention regarding e-government: Empirical evidence from China. *Information & Management*, *57*(3), 103197.
18. Li, Z., Du, N., Wang, B., & Oteng-Darko, C. (2022). Impact of social influence on users' continuance intention toward sports and fitness applications. *Frontiers in Public Health*, *10*, 1031520.
19. Lin, W. R., Lin, C. Y., & Ding, Y. H. (2020). Factors affecting the behavioral intention to adopt mobile payment: An empirical study in Taiwan. *Mathematics*, *8*(10), 1851.

20. Maria, I., Wijaya, V., & Keni, K. (2021). Pengaruh information quality dan service quality terhadap perceived value dan konsekuensinya terhadap customer engagement behavior intention (Studi pada social commerce Instagram). *Jurnal Muara Ilmu Ekonomi dan Bisnis*, *5*(2), 321-334.
21. Moorthy, K., Chun T'ing, L., Ming, K. S., Ping, C. C., Ping, L. Y., Joe, L. Q., & Jie, W. Y. (2019). Behavioral intention to adopt digital library by the undergraduates. *International Information & Library Review*, *51*(2), 128-144.
22. Naqvi, M.H.A., Jiang, Y., & Naqvi, M. (2021). Generating customer engagement in electronic- brand communities: a stimulus–organism–response perspective. Asia Pacific Journal of Marketing and Logistics. 33(7), 1535-1555.
23. Nguyen, V. T. (2021). Determinants of intention to use google lens. *Int. J. Inf. Sci. Technol*, *5*(2), 4-11.
24. Patma, T. S., Fienaningsih, N., Rahayu, K. S., & Artatanaya, I. G. L. S. (2021). Impact of Information Quality on Customer Perceived Value, Experience Quality, and Customer Satisfaction from Using GoFood Aplication. *Journal of Indonesian Economy and Business: JIEB.*, *36*(1), 51-61.
25. Purwanto, E., & Loisa, J. (2020). The intention and use behaviour of the mobile banking system in Indonesia: UTAUT Model. *Technology Reports of Kansai University*, *62*(06), 2757-2767.
26. Putri, W. K., & Pujani, V. (2019). The influence of system quality, information quality, e-service quality and perceived value on Shopee consumer loyalty in Padang City. *The International Technology Management Review*, *8*(1), 10-15.
27. Radhamani, R., Kumar, D., Nizar, N., Achuthan, K., Nair, B., & Diwakar, S. (2021). What virtual laboratory usage tells us about laboratory skill education pre-and post-COVID-19: Focus on usage, behavior, intention and adoption. *Education and information technologies*, *26*(6), 7477-7495.
28. Rahardja, U., Hongsuchon, T., Hariguna, T., & Ruangkanjanases, A. (2021). Understanding impact sustainable intention of s-commerce activities: The role of customer experiences, perceived value, and mediation of relationship quality. *Sustainability*, *13*(20), 11492.
29. Rahi, S., Ghani, M. A., & Ngah, A. H. (2020). Factors propelling the adoption of internet banking: the role of e-customer service, website design, brand image and customer satisfaction. *International Journal of Business Information Systems*, *33*(4), 549-569.
30. Rahi, S., & Ishaq, M. (2020). Factors Influencing online Shopping behavior With Mediating Role of Customer Perceived Value. *Economic and Social Development: Book of Proceedings*, 128-141.
31. Rana, S., Tandon, U., & Kumar, H. (2023). Understanding medical service quality, system quality and information quality of Tele-Health for sustainable development in the Indian context. Kybernetes.
32. Samudro, A., Sumarwan, U., Simanjuntak, M., & Yusuf, E. (2020). Assessing the effects of perceived quality and perceived value on customer satisfaction. *Management Science Letters*, *10*(5), 1077-1084.
33. Sartono, Y., Astuti, E. S., Wilopo, W., & Noerman, T. (2024). Sustainable Digital Transformation: Its Impact on Perceived Value and Adoption Intention of Industry 4.0 in Moderating Effects of Uncertainty Avoidance. *F1000Research*, *13*.
34. Senali, M.G., Cripps, H., Meek, S., & Ryan, M.M. (2022). A comparison of Australians, Chinese and Sri Lankans' payment preference at point-of-sale, Marketing Intelligence & Planning, 40(1), 18-32.
35. Sharma, N., & Fatima, J. (2024). Influence of perceived value on omnichannel usage: Mediating and moderating roles of the omnichannel shopping habit. Journal of Retailing and Consumer Services, 77, 103627.
36. Shiau, W. L., & Huang, L. C. (2023). Scale development for analyzing the fit of real and virtual world integration: an example of Pokémon Go. Information Technology & People, 36(2), 500-531.
37. Song, M., Xing, X., Duan, Y., Cohen, J., & Mou, J. (2022). Will artificial intelligence replace human customer service? The impact of communication quality and privacy risks on adoption intention. Journal of Retailing and Consumer Services, 66, 102900.
38. Sreelakshmi, C. C., & Prathap, S. K. (2023). Effect of COVID-19 health threat on consumer's perceived value towards mobile payments in India: a means-end model. *Journal of Financial Services Marketing*, 1-25.
39. Stahl, B. C. (2021). *Artificial intelligence for a better future: an ecosystem perspective on the ethics of AI and emerging digital technologies* (p. 124). Springer Nature.
40. Statista.com (2024). E-Commerce in Indonesia. Diakses dari: https://www-statista-com.translate.goog/topics/5742/e-commerce-in-indonesia/?_x_tr_sl=en&_x_tr_tl=id&_x_tr_hl=id&_x_tr_pto=tc

41. Tsai, P. H., & Tang, J. W. (2023). Consumers' switching intention towards E-commerce platforms' store-to-store pickup services: The application of the extended PPM model. Journal of Retailing and Consumer Services, 75, 103535.
42. Tseng, T.H., Lee, C.T., Huang, H.-T., & Yang, W.H. (2022). Success factors driving consumer reuse intention of mobile shopping application channel. International Journal of Retail & Distribution Management, 50(1), 76-99.
43. Tumewah, E., & Kurniawan, Y. (2020). The effect of m-banking service quality and customer perceived value to satisfaction and loyalty of bank XYZ customers. *International Journal of Management and Humanities*, *4*(6), 132-138.
44. Uzir, M. U. H., Al Halbusi, H., Thurasamy, R., Hock, R. L. T., Aljaberi, M. A., Hasan, N., & Hamid, M. (2021). The effects of service quality, perceived value and trust in home delivery service personnel on customer satisfaction: Evidence from a developing country. *Journal of Retailing and Consumer Services*, *63*, 102721.
45. Xin, B., Hao, Y., & Xie, L. (2023). Strategic product showcasing mode of E-commerce live streaming. Journal of Retailing and Consumer Services, 73, 103360.
46. Xue, L., Rashid, A. M., & Ouyang, S. (2024). The Unified Theory of Acceptance and Use of Technology (UTAUT) in Higher Education: A Systematic Review. *SAGE Open*, *14*(1), 21582440241229570.