The Impact of Social Influence on Users' Intention to Use AI Chatbots: Mediating Effects

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ABSTRACT
This study aims to explore the relationship between social influence and users' intention to use AI Chatbot services (AICSs) through the mediating roles of PE, EE, FC, HM. The survey data with the participation of 325 university students in Southern Vietnam in the form of an online survey. The research results show that social influence (SI) has a direct impact on AICS usage intention (BI), and also affects BI through the mediating roles of PE, EE, FC, HM. The research results have clarified the factors of social context and personal attributes that affect the intention to use AICSs in the current context. Therefore, these research findings are expected to provide important theoretical and practical implications for AI service developers and managers.

Keywords: *AI Chatbot services, social influence, performance expectancy, effort expectancy, hedonic motivation, behavioural intention.*

1. INTRODUCTION

AI is widely used today and is of interest to research in many fields such as medicine (Park et al., 2023), psychology (Ding & Najaf, 2024), sociology (J. S. Kim et al., 2024), economics (Qin et al., 2024), education (Crawford et al., 2024). Among the applications of AI, AI Chatbot services (AICSs) are increasingly popular due to their outstanding features. AICSs can provide transaction channel suggestions (Kushwaha & Kar, 2024), interact with customers, such as providing 24/7 operations in business transactions, and also perform specialized functions such as answering questions, analyzing, synthesizing, and writing scripts (Casheekar et al., 2024). Research on the intention to use AICSs is a topic of current interest to researchers, both positively and negatively (Sofiyah et al., 2024; Wei et al., 2024). One question is whether AI Chatbots can achieve features like ChatGPT in supporting human activities. Especially for a developing country like Vietnam, studying user intentions and examining the intention to use AICSs in the current context is a practical necessity.

Regarding the research approach, the unified theory of acceptance and use of technology (UTAUT) model is widely used to study the intention to use AICS (Camilleri, 2024; Chen et al., 2024; Liu et al., 2024; Park et al., 2024). The UTAUT model uses components such as “performance expectancy (PE), effort expectancy (EE), social influence (SI), trust (TR), perceived risk (PR), facilitating condition (FC), and extrinsic motivation (EM)”, and many studies use HM, SI, and EE as independent variables (Camilleri, 2024; Chen et al., 2024; Tian et al., 2024). SI is considered a strong factor influencing customer motivation (Pop et al., 2020), satisfaction with products or services (Xie et al., 2024). There has been no study evaluating the impact of SI on behavioral intention (BI) through the mediating role of performance expectancy (PE), effort expectancy (EE), trust (TR), perceived risk (PR), facilitating condition (FC), and extrinsic motivation (EM), which is a gap that needs to be addressed.

In this study, the Stimulus-Organism-Response (S-O-R) Theoretical Framework (Mehrabian, 1974) is used to adjust the UTAUT2 model (Venkatesh et al., 2012) into the proposed research model. The novelty of this study is to adjust the model to consider the stimulating role of the SI variable, through 4 variables performance expectancy (PE), effort expectancy (EE), facilitating condition (FC), and hedonic motivation (HM) as the Organization mechanism and the dependent variable (BI) plays the Response role. Through the mediating role for the relationships in the model, it will bring a deep understanding of customers' intention to use AICSs. The data collected from the survey will be used to analyze the PLS-SEM structural model using SmartPLS 4.1.0.0 software. Based on the analysis results, implications will be proposed to enhance customers' intention to use AICSs. The structure of this paper includes introduction, research methodology, discussion of research results, and finally conclusion.

2. RESEARCH METHODS

2.1. Theoretical framework

Behavioral intention is considered the extent to which an individual plans or desires to perform a specific action in the future. In the context of technology, it often involves using a certain application or technology platform (Venkatesh et al., 2012). Intention to use AICS is defined as "an individual's willingness to repeatedly perform specific behaviors, including using information technology applications such as AI Chatbots" (Camilleri, 2024). According to Zhao & Min (2024), intention to use AICS is approached from multiple perspectives, including perceived value and benefits, service characteristics (Soodan et al., 2024), emotions (Yue et al., 2024). Kim et al., (2009) argue that when new technologies are introduced, adoption of meaningful change such as continued use begins within the individual, and this may be influenced by how they perceive the new applications will affect their work performance. Social influence is considered the extent to which an individual perceives that others believe they should use a service (Venkatesh et al., 2012), a concept that refers to how social interactions influence a person's beliefs, attitudes, thoughts, and behaviors, specifically in the form of recommendations from friends and family.

The S-O-R model is a behavioral response mechanism through a specific stimulus that affects the psychology to give rise to response behaviors, this theory is used to explain human behavior as well as behavioral intentions (Mehrabian, 1974). In the context of AICS usage intention, the application of S-O-R to develop variables and model AICS usage intention is still limited (Rafiq et al., 2022). In studying AICS usage intention, UTAUT2 is considered a more inheritable theory and a more complete explanation of the properties of intention or behavior compared to previous models and theories such as TPB, TAM and UTAUT (Al-Adwan et al., 2024; Chen et al., 2024). Although the application of S-O-R to explain behavioral intention to use AICS is limited, S-O-R is an opportunity to construct new variables or relationships when combined with other previous theories to fully explain the mechanism of individual intention formation (Rafiq et al., 2022; Tran & Hou, 2024). By integrating the components of UTAUT2 into S-O-R, examining the mediating roles of PE, EE, FC, HM aims to address the existing gaps.

2.2. Hypothesis development

2.2.1. Relationship between SI with PE and BI

SI factor is considered important in many studies on AICS usage intention, a factor that strongly influences individual intention (Camilleri, 2024; Tian et al., 2024). PE represents the usefulness of the product in supporting users to perform a certain activity. This is the factor that has the strongest impact on behavioral intention (Venkatesh et al., 2012). Wijaya et al., (2024) also found that PE positively affects BI. This is the basis for proposing the following hypotheses:

H_{1a} : SI is positively linked with PE
H_{1b} : PE is positively linked with BI
H_{1c} : PE is mediation the link between SI and BI

2.2.2. Relationship between SI with EE and BI

Previous studies have demonstrated the influence of SI on technology adoption in different contexts (Moriuchi, 2021). Confidence in handling technical systems directly affects the intention to use them. EE is considered as a fundamental predictor of technology adoption in the research context (Wirtz et al., 2019). While Wijaya et al., (2024) found that EE does not influence BI. This is the basis for proposing the hypotheses:

H_{2a} : SI is positively linked with EE
H_{2b} : EE is positively linked with BI
H_{2c} : EE is mediation the link between SI and BI

2.2.3. Relationship between SI with FC and BI

According to Venkatesh et al. (2012), FC is the level of availability and accessibility of factors that support the use of a product. This implies that users of new technology evaluate their ability to master the technology (Wong et al., 2020), so the usefulness of technology is related to the facilitation of the user to use that technology effectively (Canziani and MacSween, 2021). In the context of intention to use AICS, there must be an infrastructure that facilitates its use (Grover et al., 2020). This is the basis for proposing the following hypotheses:

H_{3a} : SI is positively linked with FC
H_{3b} : FC is positively linked with BI
H_{3c} : FC is mediation the link between SI and BI

2.2.4. Relationship between SI with HM and BI

SI represents the impact of an individual on others, or the impact of the social environment on an individual (Tran et al., 2024). According to Venkatesh et al., (2012) definition, HM is the joy and satisfaction that users feel when using technology. Many studies have investigated the impact of SI on consumer motivation (Pop et al., 2020; Sarker et al., 2025), however, no relationship has been found between this factor affecting the intention to use AICs. The influence of HM and the intention to use AICS has been confirmed in studies (Camilleri, 2024; Paraskevi et al., 2023). This is the basis for proposing the following hypotheses:

H_{4a} : SI is positively linked with HM
H_{4b} : HM is positively linked with BI
H_{4c} : HM is mediation the link between SI and BI

2.2.5 Relationship between SI with BI

SI is "the extent to which a consumer perceives that important others (such as family and friends) believe that he or she should use a particular technology". According to Acosta-Enriquez et al. (2024), in the context of AICS use, it is the extent to which an individual perceives that important others believe that he or she should use AI. Camilleri (2024) shows that SI influences the intention to use AICS. This is the basis for proposing the hypothesis:

H_5 : SI is positively linked with BI.

2.3. Phương pháp nghiên cứu

The study uses a combination of qualitative and quantitative methods, in which the quantitative method plays a key role in testing the hypotheses in the proposed research model. The scales used in the study are inherited from Venkatesh et al. (2012) and Camilleri (2024). The survey data is in the form of online (Google Forms). The survey subjects are university students in the southern region of Vietnam. The sampling method is convenient, the sample size follows the 10-fold rule (Hair et al., 2021). A total of 500 people were sent the survey questionnaires, and 325 valid questionnaires were collected. SPSS 25.0 and SmartPLS 4.1.0.0 software were used for data analysis. Data analysis assessed two main contents: measurement model and structural model. The measurement model was evaluated through the following criteria: convergent validity (outer loadings ≥ 0.7; AVE ≥ 0.5), composite reliability (CR ≥ 0.6 or α ≥ 0.708) and discriminant validity (Fornell-Larcker, 1981). The structural model was evaluated through the following criteria: VIF, R2, f2, statistical significance of regression parameters (Hair et al., 2021).

3. RESULTS DISCUSSIONS

3.1. Measurement model analysis

The measurement model assesses convergent validity, the analysis results of the observed variables PE1, PE2, PE3, the scales achieve convergent validity. Table 1 presents the reliability and value of the main structures.

Table 1. Reliability and validity of constructs

	Cronbach's Alpha	Composite reliability (CR)	Average variance extracted (AVE)
BI	0.813	0.815	0.572
EE	0.844	0.854	0.681
FC	0.705	0.707	0.628
HM	0.899	0.899	0.831
PE	0.861	0.862	0.591
SI	0.826	0.833	0.741

The analysis results show that the reliability measurement indexes (Cronbach's Alpha & CR >0.7), AVE > 0.5 meet the requirements. Table 2 presents the discriminant validity test according to the Fornell & Larcker standard..

Table 2. Discriminant validity with Fornell & Larcker criteria

	BI	EE	FC	HM	PE	SI
BI	0.756					
EE	0.535	0.825				
FC	0.507	0.449	0.793			
HM	0.699	0.464	0.369	0.912		
PE	0.752	0.421	0.455	0.622	0.769	
SI	0.583	0.464	0.323	0.53	0.512	0.861

The results showed that the absolute values of the correlation coefficients between any pair of constructs were always less than the square root of the AVE values (on the main diagonal), concluding that the scales achieved discriminant validity (Fornell & Larcker, 1981).

3.2. Structural model analysis

The results of the structural model analysis are presented in Figure 1. The test results show that the VIF coefficients are <2, there is no multicollinearity phenomenon, the f2 values representing the predictive level of exogenous variables are in the range (0,02 < f2 < 0,391) representing a moderate and high level (Cohen, 1988). The adjusted coefficient of determination (R^2_{adj}) represents the level at which the independent variable can explain the variance of the dependent variable, is in the range (0.102< R^2_{adj}<0.697) representing a medium and high level (Chin, 1998). The conclusion is that the model meets the general suitability.

The results of the analysis of the mediation relationships presented in Table 3 show that the mediation effects are all statistically significant at the 1% level, and are fully mediated in this study.

Table 3. Results of the analysis of the mediation relationship

Associations	Path coefficient	Standard deviation	t statistics	P-values	Results
SI → PE → BI	0.208	0.032	6.530	0.000	Supported
SI → HM → BI	0.145	0.026	5.542	0.000	Supported
SI → FC → BI	0.040	0.015	2.656	0.008	Supported
SI → EE → BI	0.055	0.018	3.011	0.003	Supported

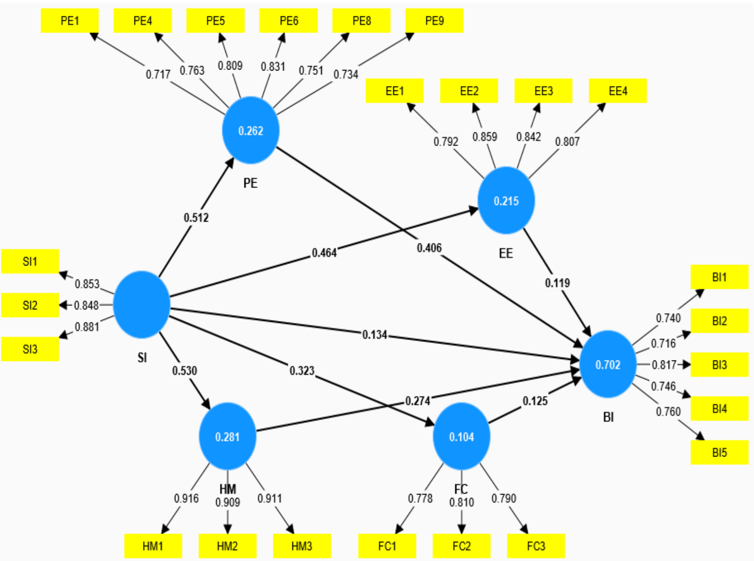

Figure 1. Results of the path coefficients

Table 4 presents the results of the total effect analysis of the hypothesized relationships in the model.

Table 4. Results of total impact test

Associations	Path coefficient	Standard deviation	t statistics	P-values	Results
EE → BI	0.119	0.038	3.146	0.002	Supported
FC → BI	0.125	0.042	2.992	0.003	Supported
HM → BI	0.274	0.042	6.475	0.000	Supported
PE → BI	0.406	0.050	8.148	0.000	Supported
SI → BI	0.583	0.039	14.895	0.000	Supported
SI → EE	0.464	0.051	9.184	0.000	Supported
SI → FC	0.323	0.059	5.498	0.000	Supported
SI → HM	0.530	0.041	12.975	0.000	Supported
SI → PE	0.512	0.048	10.653	0.000	Supported

3.3. Discussion

The study integrated some selected components in the UTAUT2 model into the S-O-R framework to study the intention to use AICS. The relationships in the theoretical model have a high level of statistical significance, explaining the intention to use AICS (R^2_{adj} = 69,7%). Some issues need to be discussed in this study.

In the relationships, SI direct impact on the mediating variables is strong, the strongest is HM (β= 0.530, p < 0,01), the weakest is FC (β= 0.323, p < 0,01). For the direct relationships on BI, the strongest impact is PE (β= 0.406, p < 0,01) and the weakest is EE (β= 0.119, p < 0,01). SI has the strongest direct impact on BI (β= 0.583, p < 0,01). This result confirms the positive influence of SI on the intention to use AICS, consistent with the studies of Camilleri (2024) and Biloš and Budimir (2024). This result shows that the opinions of people around, from the social environment, have an impact on the inner self of individuals, creating expectations and motivations that urge them to accept and lead to the intention to use technological advances. From the results of this study, managers need to clearly define the goals when building policies, need to understand the relationship between stimuli that affect internal transformations, thereby motivating them to act.

The mediating role of the variables PE, EE, FC and HM in this study is considered a new point. The mediating relationships have different levels of impact, the strongest is SI → PE → BI (β= 0.208, p < 0.01) and the weakest is SI → FC → BI (β= 0.040, p < 0.01). Previous studies on AICS often use PE, EE, FC and HM as independent variables, which directly affect BI (Chen et al., 2024; Xu et al., 2024). Some studies have examined the mediating effect such as Camilleri (2024) concluding that there is a mediating relationship between EE and BI through PE; or Sitar-Tăut (2021) examining the mediating role of HM in the relationship with BI. This research result further clarifies the rather multidimensional relationship in the research model, through the intermediary relationships will increase consumers' intention to use AICS.

4. CONCLUSION

The study selectively integrated the factors in the UTAUT2 model with the S-O-R framework to build a research model; in which SI is identified as Stimulus; PE, EE, FC and HM are identified as Organism with a mediating role and BI is Response. The research results confirm that the intention to use AICS is formed through users' perceptions of the attributes of SI, PE, EE, FC and HM that directly and indirectly affect the intention to use. The results of this study aim to provide guidance for the use of AICS for many different fields related to technology such as health, business, smart home systems, personalized bot assistants, etc., showing that personal factors are important variables for an integrated framework, the dependent relationship between the use of technology in the social context, within the framework of the country of Vietnam.

REFERENCES

Acosta-Enriquez, B. G., Farroñan, E. V. R., Zapata, L. I. V., Garcia, F. S. M., Rabanal-León, H. C., Angaspilco, J. E. M., & Bocanegra, J. C. S. (2024). Acceptance of artificial intelligence in university contexts: A conceptual analysis based on UTAUT2 theory. *Heliyon*. https://doi.org/10.1016/j.heliyon.2024.e38315

Al-Adwan, A. S., Jafar, R. M. S., & Sitar-Tăut, D.-A. (2024). Breaking into the black box of consumers' perceptions on metaverse commerce: An integrated model of UTAUT 2 and dual-factor theory. *Asia Pacific Management Review*. https://doi.org/10.1016/j.apmrv.2024.09.004

Biloš, A., & Budimir, B. (2024). Understanding the Adoption Dynamics of ChatGPT among Generation Z: Insights from a Modified UTAUT2 Model. *Journal of theoretical and applied electronic commerce research*, *19*(2), 863-879. https://doi.org/10.3390/jtaer19020045

Camilleri, M. A. (2024). Factors affecting performance expectancy and intentions to use ChatGPT: Using SmartPLS to advance an information technology acceptance framework. *Technological Forecasting and Social Change*, *201*, 123247. https://doi.org/10.1016/j.techfore.2024.123247

Canziani, B., & MacSween, S. (2021). Consumer acceptance of voice-activated smart home devices for product information seeking and online ordering. *Computers in Human Behavior*, 119, 106714. https://doi.org/10.1016/j.chb.2021.106714

Casheekar, A., Lahiri, A., Rath, K., Prabhakar, K. S., & Srinivasan, K. (2024). A contemporary review on chatbots, AI-powered virtual conversational agents, ChatGPT: Applications, open challenges and future research directions. *Computer Science Review*, *52*, 100632. https://doi.org/10.1016/j.cosrev.2024.100632

Chen, G., Fan, J., & Azam, M. (2024). Exploring artificial intelligence (AI) chatbots adoption among research scholars using unified theory of acceptance and use of technology (UTAUT). *Journal of Librarianship and Information Science*, 1–19. https://doi.org/10.1177/09610006241269189

Crawford, J., Allen, K.-A., Pani, B., & Cowling, M. (2024). When artificial intelligence substitutes humans in higher education: the cost of loneliness, student success, and retention. *Studies in Higher Education*, *49*(5), 883-897. https://doi.org/10.1080/03075079.2024.2326956

Ding, Y., & Najaf, M. (2024). Interactivity, humanness, and trust: a psychological approach to AI chatbot adoption in e-commerce. *BMC psychology*, *12*(1), 595. https://doi.org/10.1186/s40359-024-02083-z

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of marketing research*, 18(1), 39-50. https://doi.org/10.1177/002224378101800104

Grover, T., Rowan, K., Suh, J., McDuff, D., & Czerwinski, M. (2020, March). Design and evaluation of intelligent agent prototypes for assistance with focus and productivity at work. In *Proceedings of the 25th international conference on intelligent user interfaces* (pp. 390-400). https://doi.org/10.1145/3377325.3377507

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*. Springer Nature. https://doi.org/10.1007/978-3-030-80519-7

Kim, J. S., Kim, M., & Baek, T. H. (2024). Enhancing User Experience With a Generative AI Chatbot. *International Journal of Human–Computer Interaction*, 1-13. https://doi.org/10.1080/10447318.2024.2311971

Kushwaha, A. K., & Kar, A. K. (2024). MarkBot–a language model-driven chatbot for interactive marketing in post-modern world. *Information systems frontiers*, *26*(3), 857-874. https://doi.org/10.1007/s10796-021-10184-y

Liu, M., Yang, Y., Ren, Y., Jia, Y., Ma, H., Luo, J., Fang, S., Qi, M., & Zhang, L. (2024). What influences consumer AI chatbot use intention? An application of the extended technology acceptance model. *Journal of Hospitality and Tourism Technology*, *15*(4), 667-689. https://doi.org/10.1108/JHTT-03-2023-0057

Mehrabian, A. (1974). An approach to environmental psychology. *Massachusetts Institute of Technology*.

Moriuchi, E. (2021). An empirical study on anthropomorphism and engagement with disembodied AIs and consumers' re-use behavior. *Psychology & Marketing*, 38(1), 21-42. https://doi.org/10.1002/mar.21407

Qin, Y., Xu, Z., Wang, X., & Skare, M. (2024). Artificial intelligence and economic development: An evolutionary investigation and systematic review. *Journal of the Knowledge Economy*, *15*(1), 1736-1770. https://doi.org/10.1007/s13132-023-01183-2

Paraskevi, G., Saprikis, V., & Avlogiaris, G. (2023). Modeling Nonusers' Behavioral Intention towards Mobile Chatbot Adoption: An Extension of the UTAUT2 Model with Mobile Service Quality Determinants. *Human Behavior and Emerging Technologies*, *2023*(1), 8859989. https://doi.org/10.1155/2023/8859989

Park, G., Chung, J., & Lee, S. (2023). Effect of AI chatbot emotional disclosure on user satisfaction and reuse intention for mental health counseling: a serial mediation model. *Current Psychology*, *42*(32), 28663-28673. https://doi.org/10.1007/s12144-022-03932-z

Park, Y., Kim, J., Jiang, Q., & Kim, K. H. (2024). Impact of artificial intelligence (AI) chatbot characteristics on customer experience and customer satisfaction. *Journal of Global Scholars of Marketing Science*, *34*(3), 439-457. https://doi.org/10.1080/21639159.2024.2362654

Pop, R.-A., Săplăcan, Z., & Alt, M.-A. (2020). Social media goes green—The impact of social media on green cosmetics purchase motivation and intention. *Information*, *11*(9), 447. https://doi.org/10.3390/info11090447

Rafiq, F., Dogra, N., Adil, M., & Wu, J.-Z. (2022). Examining consumer's intention to adopt AI-chatbots in tourism using partial least squares structural equation modeling method. *Mathematics*, *10*(13), 2190. https://doi.org/10.3390/math10132190

Sarker, R., Currie, G., & Reynolds, J. (2025). The pandemic is over but riders still fear infection− An extended behavioural model explaining post-pandemic transit avoidance related to perceived infection fear. *Transportation Research Part A: Policy and Practice*, *192*, 104363. https://doi.org/10.1016/j.tra.2024.104363
Sitar-Tăut, D. A. (2021). Mobile learning acceptance in social distancing during the COVID-19 outbreak: The mediation effect of hedonic motivation. *Human Behavior and Emerging Technologies*, *3*(3), 366-378. https://doi.org/10.1002/hbe2.261
Sofiyah, F. R., Dilham, A., Hutagalung, A. Q., Yulinda, Y., Lubis, A. S., & Marpaung, J. L. (2024). The chatbot artificial intelligence as the alternative customer services strategic to improve the customer relationship management in real-time responses. *International Journal of Economics and Business Research*, *27*(5), 45-58. https://doi.org/10.1504/IJEBR.2024.139810
Tian, W., Ge, J., Zhao, Y., & Zheng, X. (2024). AI Chatbots in Chinese higher education: adoption, perception, and influence among graduate students—an integrated analysis utilizing UTAUT and ECM models. *Frontiers in Psychology*, *15*, 1268549. https://doi.org/10.3389/fpsyg.2024.1268549
Tran, T. A. P., & Hou, X. (2024). Enterprise Innovation Decision-Making Towards Green and Sustainability from the Perspective of Cognitive Innovation. *Emerging Science Journal*, *8*(6), 2360-2372. https://doi.org/10.28991/ESJ-2024-08-06-013
Tran, T. D., Doan, H. T., Van Pham, T., & Truong, T. M. T. (2024). Social influences, cognitive competence, problem-solving skills: A case study of problem-solving skills in the context of digitalization adoption. *International Journal of Instruction*, *17*(4), 195-218. https://doi.org/10.29333/iji.2024.17412a
Venkatesh, V., Thong, J. Y., & Xu, X. (2012). Consumer acceptance and use of information technology: extending the unified theory of acceptance and use of technology. *MIS quarterly*, 157-178. https://doi.org/10.2307/41410412
Wei, X., Chu, X., Geng, J., Wang, Y., Wang, P., Wang, H., Wang, C., & Lei, L. (2024). Societal impacts of chatbot and mitigation strategies for negative impacts: A large-scale qualitative survey of ChatGPT users. *Technology in Society*, *77*, 102566. https://doi.org/10.1016/j.techsoc.2024.102566
Wijaya, T. T., Su, M., Cao, Y., Weinhandl, R., & Houghton, T. (2024). Examining Chinese preservice mathematics teachers' adoption of AI chatbots for learning: Unpacking perspectives through the UTAUT2 model. *Education and Information Technologies*, 1-29. https://doi.org/10.1007/s10639-024-12837-2
Wirtz, B. W., Weyerer, J. C., & Geyer, C. (2019). Artificial intelligence and the public sector—applications and challenges. International Journal of Public Administration, 42(7), 596-615. https://doi.org/10.1080/01900692.2018.1498103
Wong, L. W., Leong, L. Y., Hew, J. J., Tan, G. W. H., & Ooi, K. B. (2020). Time to seize the digital evolution: Adoption of blockchain in operations and supply chain management among Malaysian SMEs. International Journal of Information Management, 52, 101997. https://doi.org/10.1016/j.ijinfomgt.2019.08.005
Xie, Y., Liang, C., Zhou, P., & Jiang, L. (2024). Exploring the influence mechanism of chatbot-expressed humor on service satisfaction in online customer service. *Journal of Retailing and Consumer Services*, *76*, 103599. https://doi.org/10.1016/j.jretconser.2023.103599
Xu, S., Chen, P., & Zhang, G. (2024). Exploring Chinese University Educators' Acceptance and Intention to Use AI Tools: An Application of the UTAUT2 Model. *SAGE Open*, *14*(4), 21582440241290013. https://doi.org/10.1177/21582440241290013
Yue, Y., Ng, S. I., & Basha, N. K. (2024). Consumption values, attitudes and continuance intention to adopt ChatGPT-driven e-Commerce AI Chatbot (LazzieChat). *Pakistan Journal of Commerce and Social Sciences (PJCSS)*, *18*(2), 249-284.
Zhao, H., & Min, Q. (2024). Exploring continued usage of an AI teaching assistant among university students: A temporal distance perspective. *Information & Management*, *61*(6), 104012. https://doi.org/10.1016/j.im.2024.104012