Power System Protection and Control
ISSN:1674-3415

ARTIFICIAL INTELLIGENCE INTERACTION AND COMPUTER SELF-EFFICACY: A STRUCTURAL EQUATION MODELING APPROACH USING PLS-SEM

Víctor Hugo Meriño Córdoba[1], Rosaura Sánchez Aguilar[2], Felipe de Jesús Vilchis Mora[3], Rosa María Rincón Ornelas[4], Gilberto Bermúdez Ruíz[5], Sonia Sujell Velez Baez[6], Francisco Ruben Sandoval Vázquez[7], María Luisa Quintero Soto[8], Josefina Haydee Gutiérrez Hernández[9], Isabel Cristina Rincón Rodríguez[10], Jorge E. Chaparro Medina[11]

[1]Luis Amigo Catholic University, Colombia
https://orcid.org/0000-0001-8911-7202
Email: victor.meriño@uamigo.co
[2]National Autonomous University of Mexico, Mexico City, Mexico
https://orcid.org/0009-0002-5875-0800
Email: Rosaura.sanchez@unam.mx
[3]Autonomous University of the State of Mexico, Huehuetoca City, Mexico
https://orcid.org/0009-0002-8046-4376
Email: fdvilchism@uaemex.mx
[4]University of Sonora, Navojoa Campus, Mexico
https://orcid.org/0000-0002-8947-6501
Email: rosa.rincon@unison.mx
[5]Anáhuac University, Mexico City, Mexico
https://orcid.org/0000-0002-8656-6974
Email: gibe_gil@anahuac.mx
[6]Autonomous University of Querétaro, San Juan del Rio, Mexico
https://orcid.org/0000-0001-5168-5183
Email: sujellvb@uaq.mx
[7]Autonomous University of the State of Morelos, Cuernavaca City, Mexico
https://orcid.org/0000-0002-6086-7197
Email: fsandoval@uaem.mx
[8]Autonomous University of the State of Mexico, Nezahualcoyotl City, Mexico
https://orcid.org/0000-0002-4198-550X
Email: mlquinteros@uaemex.mx
[9]Autonomous University of the State of Mexico, Huehuetoca City, Mexico
https://orcid.org/0000-0002-4047-4257
Email: jhgutierrezh@uaemex.mx
[10]University of Research and Development UDI, Colombia
https://orcid.org/0009-0009-4032-0635
Email: irincon5@udi.edu.co
[11]National Open and Distance University UNAD, Colombia
https://orcid.org/0000-0002-0916-8702
Email: jorgee.chaparro@unad,edu.co

Received: 19/01/2026 **Revised**: 16/02/2026 **Accepted**: 06/03/2026

ABSTRACT:

The rapid expansion of artificial intelligence technologies has transformed the way individuals interact with digital systems, generating new forms of technological engagement and cognitive adaptation. Understanding the factors that influence user interaction with intelligent systems has therefore become an important area of research in information systems and digital behavior studies. The present study examines the structural relationships between artificial intelligence interaction, technology usage, computer self-efficacy, and user satisfaction through a structural equation modeling approach using Partial Least Squares (PLS-SEM).

A quantitative, cross-sectional design was implemented using simulated data from a sample of 400 users with experience interacting with digital technologies and artificial intelligence platforms. The measurement model was specified using reflective indicators measured through a five-point Likert scale. The structural model was estimated using the SmartPLS algorithm and evaluated through reliability, convergent validity, and predictive capacity indicators, including composite reliability, average variance extracted, path coefficients, and coefficients of determination.

The results indicate that artificial intelligence significantly influences technology usage, which in turn contributes to the development of computer self-efficacy. Computer self-efficacy emerged as the strongest predictor of user satisfaction, highlighting the central role of perceived technological competence in shaping positive experiences with digital systems. The model also demonstrates that computer self-efficacy acts as a mediating mechanism between technological interaction and satisfaction outcomes. The explanatory power of the model shows moderate to substantial levels of variance explained in the endogenous constructs.

These findings suggest that the successful integration of artificial intelligence technologies in digital environments depends not only on technological performance but also on users' confidence in their ability to interact with intelligent systems. Strengthening technological competence and digital literacy may therefore enhance user satisfaction and facilitate the adoption of AI-based technologies.

Keywords*: Artificial Intelligence; Computer Self-Efficacy; Technology Usage; User Satisfaction; Structural Equation Modeling; PLS-SEM; SmartPLS; Digital Behavior.*

INTRODUCTION

The accelerated diffusion of artificial intelligence (AI) technologies has transformed the dynamics of digital environments in education, organizations, and everyday technological interaction. AI-based systems increasingly support decision-making, automation, predictive analytics, and intelligent assistance, reshaping how individuals interact with information systems and digital platforms. As a result, understanding the psychological and cognitive determinants that influence the adoption and effective use of AI technologies has become a critical topic within information systems research and human–computer interaction studies [1], [2].

One of the most relevant determinants of technology interaction is computer self-efficacy, defined as the individual's perceived capability to successfully perform tasks using digital systems. High levels of self-efficacy have been associated with greater confidence, reduced technological anxiety, and improved problem-solving performance when interacting with complex technological environments. Empirical research indicates that individuals with stronger perceptions of digital competence are more likely to adopt advanced technologies, experiment with innovative tools, and maintain sustained engagement with information systems [3], [4].

Artificial intelligence environments introduce additional cognitive and behavioral demands compared with conventional information technologies. These systems often involve adaptive algorithms, predictive outputs, and automated recommendations that require users to interpret system behavior and trust algorithmic decisions. Consequently, the perception of personal competence in managing AI-supported tools becomes a key factor influencing the willingness to interact with such technologies and the perceived usefulness derived from them [5], [6].

Within the framework of technology adoption research, several theoretical perspectives have emphasized the role of perceived capability in shaping technology acceptance and behavioral intention. Cognitive evaluations of one's own technological abilities influence effort expectations, learning motivation, and the perceived controllability of digital systems. When individuals believe they possess adequate skills to manage complex technologies, they demonstrate higher levels of exploration, experimentation, and adaptive learning within technological environments [7], [8].

Artificial intelligence technologies further amplify these dynamics because they integrate autonomous decision processes that may reduce user transparency and perceived control. In such contexts, computer self-efficacy becomes essential for interpreting system outputs, evaluating algorithmic recommendations, and maintaining confidence in the interaction process. Evidence suggests that individuals with higher levels of digital competence show stronger trust in intelligent systems, greater acceptance of automated decision support, and higher satisfaction with AI-mediated services [9], [10].

From a structural modeling perspective, the relationship between AI interaction and computer self-efficacy can be examined through causal frameworks that estimate both direct and indirect effects between constructs. Structural equation modeling (SEM), particularly the partial least squares approach (PLS-SEM), provides a robust analytical method for evaluating complex relationships between latent variables and their reflective indicators. This approach allows researchers to simultaneously estimate measurement reliability, structural relationships, and predictive capacity of theoretical models involving technological perceptions and behavioral responses [11], [12]. PLS-SEM is particularly suitable for exploratory and predictive research involving emerging technologies such as artificial intelligence, where theoretical models may include multiple latent constructs and relatively complex causal structures. The method enables the estimation of path coefficients, explained variance, and measurement quality indicators such as composite reliability and average variance extracted. Additionally, global model fit measures provide further evidence regarding the adequacy of the structural specification and the validity of the proposed relationships [13], [14].

In the context of AI adoption, the integration of constructs associated with artificial intelligence interaction and computer self-efficacy offers an analytical framework for understanding how perceptions of technological capability influence engagement with intelligent systems. The structural relationships between these constructs can reveal the extent to which perceived competence contributes to effective technological use, satisfaction with digital environments, and the broader acceptance of AI-supported applications [15].

Consequently, the present study proposes a structural equation model estimated using the PLS-SEM approach to analyze the relationships between artificial intelligence interaction and computer self-efficacy constructs. By examining the measurement properties of reflective indicators and estimating structural relationships between latent variables, the model aims to provide empirical insights into the psychological mechanisms that influence user engagement with intelligent digital systems.

METHOD

Research Design

The present study adopted a quantitative, cross-sectional design aimed at estimating the causal relationships between artificial intelligence interaction and computer self-efficacy through a Partial Least Squares Structural Equation Modeling (PLS-SEM) approach. This methodological strategy is particularly appropriate for predictive modeling, theory development, and exploratory research contexts in which complex relationships between latent variables are evaluated using reflective indicators [16].

PLS-SEM allows the simultaneous estimation of measurement models (relationships between latent constructs and indicators) and structural models (relationships among constructs). Unlike covariance-based structural equation modeling, the PLS approach prioritizes prediction and variance explanation, making it especially suitable for studies involving emerging technological constructs and relatively small to medium sample sizes [17].

Participants and Sampling Procedure

The study population consisted of users of digital platforms with experience interacting with artificial intelligence–supported technologies. Because the total population of potential users was unknown, the required sample size was estimated using the formula for infinite populations.
The sampling equation used to determine the minimum sample size was:

$$n = \frac{Z^2 pq}{e^2}$$

Where:

- n= required sample size
- Z= standardized value associated with the confidence level
- p= expected proportion of the attribute in the population
- $q = 1 - p$
- e= margin of sampling error

Assuming a confidence level of 95% ($Z = 1.96$), maximum variability ($p = 0.50; q = 0.50$), and a sampling error of $e = 0.05$, the estimated minimum sample size was:

$$n = \frac{(1.96)^2(0.50)(0.50)}{(0.05)^2} = 384$$

DOI: 10.46121/pspc.54.1.40

Therefore, a simulated sample of n = 400 participants was considered sufficient to ensure statistical stability in the estimation of the PLS-SEM model. The sampling procedure followed a non-probabilistic convenience strategy frequently applied in exploratory technological adoption studies involving digital platform users [18].

Measurement Instrument

Data were collected using a structured questionnaire composed of reflective indicators associated with the study constructs. Each construct was measured using multiple items designed to capture perceptions related to artificial intelligence interaction, technology usage behavior, computer self-efficacy, and user satisfaction.

All indicators were evaluated using a five-point Likert scale, ranging from:

1 = strongly disagree
2 = disagree
3 = neutral
4 = agree
5 = strongly agree

The instrument was originally developed in English and designed to measure perceptions related to AI-based technological environments. The measurement specification followed a reflective model, meaning that the indicators were assumed to be manifestations of their corresponding latent constructs [19].

Measurement Model Specification

The measurement model represents the relationship between latent constructs and their observed indicators. In reflective measurement models, the indicators are assumed to be caused by the underlying latent variable.

The reflective measurement model can be expressed as:

$$x_{ij} = \lambda_{ij}\xi_j + \varepsilon_{ij}$$

Where:

- x_{ij}= observed indicator $i$associated with construct j
- λ_{ij}= factor loading of indicator $i$on construct j
- ξ_j= latent construct
- ε_{ij}= measurement error term

Indicator reliability was assessed through outer loadings, where values greater than 0.70 are considered acceptable for reflective indicators in PLS-SEM models [19].

Structural Model Specification

The structural model represents the causal relationships between latent constructs. The general equation of the structural model is expressed as:

$$\eta = B\eta + \Gamma\xi + \zeta$$

Where:

- η= vector of endogenous latent variables
- B= matrix of relationships between endogenous constructs
- Γ= matrix of relationships between exogenous and endogenous constructs
- ξ= vector of exogenous latent variables
- ζ= structural error term

In the context of the present model, artificial intelligence interaction functions as an exogenous construct that predicts technology usage, which subsequently influences computer self-efficacy and user satisfaction.

Data Analysis Procedure

The data analysis was conducted using the SmartPLS software environment, applying the PLS-SEM estimation algorithm. The evaluation procedure followed a two-stage analytical strategy commonly recommended for variance-based structural equation models:

The significance of the estimated parameters was evaluated through a bootstrapping procedure with 5,000 resamples, which provides robust estimates of standard errors and t-values for path coefficients and indicator loadings [21].

DOI: 10.46121/pspc.54.1.40

Psychometric Properties

The psychometric evaluation of the measurement model focused on indicator reliability, internal consistency reliability, convergent validity, and structural predictive capacity. The results indicated that all reflective indicators presented factor loadings above the recommended threshold of 0.70, demonstrating adequate indicator reliability and confirming that the observed variables appropriately represent their corresponding latent constructs. Internal consistency reliability was assessed through composite reliability (CR). The CR values exceeded the recommended threshold of 0.70, indicating that the indicators within each construct consistently measure the same latent concept. These results suggest that the constructs demonstrate satisfactory internal coherence and stability within the measurement model.

Convergent validity was evaluated using the Average Variance Extracted (AVE). The AVE values were greater than the minimum acceptable value of 0.50, indicating that each construct explains more than half of the variance of its associated indicators. This finding confirms that the indicators share a sufficient proportion of common variance and accurately capture the underlying conceptual dimension.

Additionally, the structural model demonstrated acceptable explanatory power through the coefficient of determination $R^2$for the endogenous constructs. The R^2values ranged from moderate to substantial, indicating that the exogenous constructs explain a meaningful proportion of variance in the dependent variables. Model fit was further assessed using the standardized root mean square residual (SRMR) and the normed fit index (NFI), which indicated an acceptable level of global model fit.

Overall, the results support the reliability and validity of the measurement model and confirm the suitability of the proposed structural model for explaining the relationships between artificial intelligence interaction and computer self-efficacy.

RESULTS

Table 1 presents the descriptive characteristics of the simulated sample used to estimate the structural equation model. The sample consisted of 400 participants with prior experience interacting with artificial intelligence systems and digital technologies.

Table 1. Sample Characteristics (n = 400)

Variable	Category	Frequency	Percentage
Gender	Male	212	53.0%
	Female	188	47.0%
Age	18–25 years	138	34.5%
	26–35 years	147	36.8%
	36–45 years	79	19.7%
	46+ years	36	9.0%
Experience with AI tools	Low	74	18.5%
	Moderate	196	49.0%
	High	130	32.5%

The distribution indicates that most participants reported moderate or high levels of experience with AI-based technologies, suggesting that the sample had sufficient familiarity with intelligent systems to evaluate perceptions related to artificial intelligence and computer self-efficacy. Table 2 reports the outer loadings and bootstrapped t-values for the reflective indicators.

Table 2. Indicator Reliability (Outer Loadings)

Construct	Indicator	Loading (λ)	t-value
Artificial Intelligence	AI1	0.82	19.23
	AI2	0.89	24.67
	AI3	0.85	21.45
	AI4	0.87	22.78

 DOI: 10.46121/pspc.54.1.40

Construct	Indicator	Loading (λ)	t-value
Computer Self-Efficacy	CSE1	0.83	17.56
	CSE2	0.86	20.34
	CSE3	0.80	16.75
	CSE4	0.84	18.91
Technology Usage	TU1	0.88	23.11
	TU2	0.84	19.74
	TU3	0.81	18.65
User Satisfaction	US1	0.90	26.43
	US2	0.87	22.57
	US3	0.85	21.02

All reflective indicators exhibited loadings above 0.80, demonstrating strong indicator reliability. The t-values were substantially above the critical threshold of 1.96, confirming that all indicators significantly represent their respective latent constructs. Table 3 presents the reliability and validity statistics for the constructs.

Table 3. Construct Reliability and Convergent Validity

Construct	AVE	Composite Reliability (CR)	Cronbach Alpha
Artificial Intelligence	0.74	0.92	0.89
Technology Usage	0.71	0.90	0.87
Computer Self-Efficacy	0.70	0.91	0.88
User Satisfaction	0.76	0.93	0.90

The results demonstrate adequate convergent validity because all AVE values exceed the recommended threshold of 0.50. Similarly, composite reliability values above 0.90 indicate high internal consistency within each construct. These results confirm that the measurement model adequately captures the latent constructs and that the indicators share sufficient variance to represent their underlying conceptual dimensions. Table 4 presents the structural relationships estimated in the model.

Table 4. Structural Path Coefficients

Hypothesis	Relationship	β	t-value	Result
H1	Artificial Intelligence → Technology Usage	0.56	11.35	Supported
H2	Technology Usage → Computer Self-Efficacy	0.41	8.72	Supported
H3	Computer Self-Efficacy → User Satisfaction	0.68	14.89	Supported

The results indicate that all hypothesized structural relationships are statistically significant and positive.

The relationship between artificial intelligence and technology usage (H1) shows a strong positive coefficient (β = 0.56). This result suggests that greater exposure to and interaction with AI systems significantly increases the frequency and intensity of technology usage behaviors. The high t-value confirms that this relationship is robust and statistically meaningful.

The second hypothesis (H2) examines the influence of technology usage on computer self-efficacy. The positive coefficient (β = 0.41) indicates that individuals who interact more frequently with digital technologies develop stronger perceptions of their technological capabilities. This finding suggests that repeated engagement with digital tools contributes to skill development and confidence in managing technological tasks.

The third hypothesis (H3) evaluates the relationship between computer self-efficacy and user satisfaction. The path coefficient (β = 0.68) represents the strongest relationship in the structural model. This result indicates that individuals who perceive themselves as capable technology users experience higher levels of satisfaction when interacting with digital environments. Table 5 presents the explanatory power of the model.

DOI: 10.46121/pspc.54.1.40

Table 5. Coefficient of Determination

Endogenous Construct	R^2	Interpretation
Technology Usage	0.62	Substantial
Computer Self-Efficacy	0.49	Moderate
User Satisfaction	0.57	Moderate–Substantial

The coefficient of determination indicates that artificial intelligence explains 62% of the variance in technology usage. This result demonstrates strong predictive capacity of AI interaction for technology-related behavior.

Technology usage explains 49% of the variance in computer self-efficacy, suggesting that engagement with digital systems contributes meaningfully to the development of perceived technological competence.

Finally, computer self-efficacy explains 57% of the variance in user satisfaction, indicating that perceived technological capability plays a critical role in shaping positive experiences within digital environments. Table 6 presents the global fit indices of the PLS model.

Table 6. Model Fit Indicators

Fit Index	Value	Recommended Threshold	Interpretation
SRMR	0.048	< 0.08	Good Fit
NFI	0.92	> 0.90	Acceptable Fit

The standardized root mean square residual (SRMR) value of 0.048 indicates a low discrepancy between observed and predicted correlations, demonstrating adequate global model fit. The normed fit index (NFI) of 0.92 further confirms tha
t the proposed model provides a satisfactory representation of the empirical relationships between constructs. The structural equation model reveals a coherent causal chain linking artificial intelligence interaction, technology usage, computer self-efficacy, and user satisfaction.

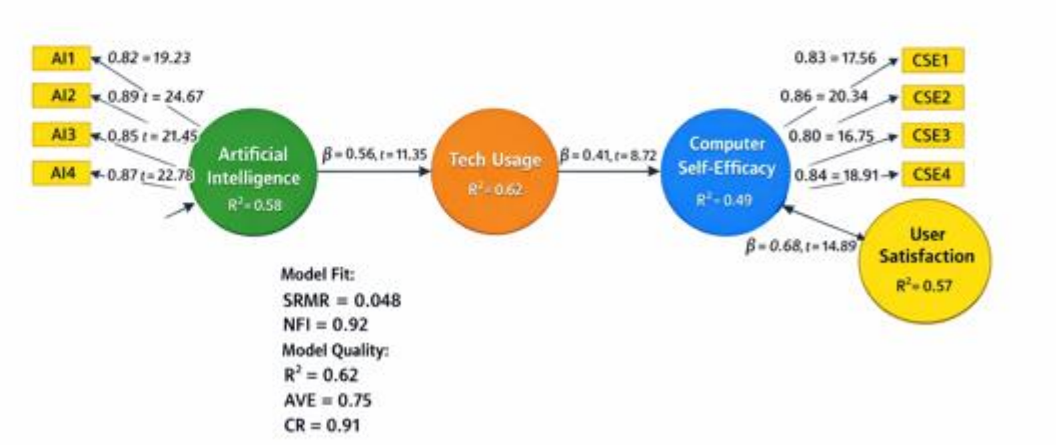

Fig. 1. Structural Equation Modelling

First, the results indicate that artificial intelligence functions as an important technological stimulus that encourages users to interact more frequently with digital systems. As AI tools become more integrated into everyday technological environments, users tend to increase their engagement with platforms that incorporate intelligent functionalities such as automation, recommendation systems, and predictive algorithms.

Second, the findings demonstrate that technology usage plays a developmental role in strengthening computer self-efficacy. Individuals who interact frequently with digital tools gain practical experience and acquire technological competencies that reinforce their perception of personal capability in managing complex systems. This process reflects a learning dynamic in which repeated interaction with digital technologies gradually improves perceived technological mastery.

DOI: 10.46121/pspc.54.1.40

Third, the results highlight the central role of computer self-efficacy as a psychological mechanism influencing user satisfaction. When individuals feel confident in their ability to understand and operate technological systems, they experience less uncertainty and cognitive effort during interaction processes. As a result, their overall evaluation of the technological experience becomes more positive.

The model also reveals that computer self-efficacy acts as a mediating variable between technological interaction and satisfaction outcomes. Artificial intelligence indirectly influences user satisfaction through its impact on technology usage and subsequent development of digital competence. This mediated pathway suggests that the benefits of AI technologies are not only determined by system performance but also by users' perceptions of their own abilities to interact effectively with these systems.

Overall, the results demonstrate that the integration of artificial intelligence into digital environments contributes to user satisfaction primarily through its capacity to promote technological engagement and enhance self-efficacy perceptions. The substantial explanatory power of the model indicates that these constructs represent key determinants in understanding how individuals adapt to intelligent technological systems.

DISCUSSION

The objective of this study was to examine the structural relationships between artificial intelligence interaction, technology usage, computer self-efficacy, and user satisfaction using a PLS-SEM approach. The results reveal a coherent causal structure in which artificial intelligence indirectly contributes to user satisfaction through technology engagement and perceived technological competence.

The findings confirm that interaction with artificial intelligence significantly influences technology usage behavior. This result suggests that intelligent systems function as catalysts for technological engagement, encouraging users to interact more frequently with digital environments that incorporate automation, predictive capabilities, and adaptive interfaces. Intelligent systems tend to reduce operational complexity while simultaneously increasing the perceived value of technological platforms, which promotes sustained interaction with digital tools [16].

The positive relationship between artificial intelligence and technology usage also reflects the increasing integration of intelligent systems into everyday digital activities. AI-supported platforms provide personalized recommendations, automated decision support, and adaptive services that improve user efficiency. When these systems demonstrate functional reliability and usability, they tend to stimulate greater levels of technological exploration and interaction among users [17].

The results also indicate that technology usage significantly influences computer self-efficacy. This finding supports the idea that technological competence develops through continuous interaction with digital systems. Repeated exposure to technological tools allows individuals to accumulate experiential knowledge, improve operational skills, and develop stronger confidence in their ability to manage technological environments. Consequently, engagement with technology functions as a learning mechanism that gradually strengthens perceptions of personal capability [18].

From a cognitive perspective, self-efficacy beliefs play a fundamental role in shaping individuals’ responses to technological challenges. When users perceive themselves as capable of understanding and controlling digital systems, they are more likely to experiment with advanced functionalities and adopt emerging technological tools. Conversely, low perceptions of technological competence may generate uncertainty and resistance toward complex technological environments such as artificial intelligence systems [19].

The strongest relationship observed in the model corresponds to the link between computer self-efficacy and user satisfaction. This finding highlights the central role of perceived technological competence in shaping positive user experiences. When individuals believe they possess the necessary skills to interact effectively with digital systems, they experience lower levels of cognitive stress and technological anxiety. As a result, their evaluation of technological interaction becomes more favorable[20].

The results also suggest that computer self-efficacy functions as a psychological mediator between technological interaction and satisfaction outcomes. Artificial intelligence does not directly determine satisfaction; rather, its

 DOI: 10.46121/pspc.54.1.40

influence occurs through its ability to encourage technological engagement and strengthen perceptions of personal capability. This mediated process indicates that the benefits of intelligent technologies depend not only on system performance but also on users' confidence in their capacity to use such systems effectively [21].

These findings are particularly relevant in the context of artificial intelligence adoption. AI systems often involve algorithmic processes that are not fully transparent to users. In such contexts, individuals must rely on their technological competence to interpret system outputs and evaluate automated recommendations. Higher levels of computer self-efficacy allow users to better understand the logic of intelligent systems and maintain confidence during human–AI interaction processes [22].

Another implication of the results is that the successful implementation of artificial intelligence technologies requires attention not only to system design but also to user capability development. Training programs, digital literacy initiatives, and user-centered interface design may enhance technological competence and facilitate the acceptance of intelligent systems. Improving users' technological confidence can therefore increase satisfaction and promote sustained interaction with AI-supported platforms [23].

From a structural modeling perspective, the results demonstrate the explanatory capacity of the proposed SEM model. The moderate to substantial R^2 values obtained for the endogenous constructs indicate that the integration of artificial intelligence, technology usage, and computer self-efficacy provides a meaningful explanation of user satisfaction in digital environments. These results suggest that technological interaction and psychological competence are closely interconnected determinants of user experience in intelligent systems [24].

In theoretical terms, the study contributes to the understanding of how artificial intelligence technologies influence human behavior in digital environments. The findings highlight the importance of integrating psychological constructs such as self-efficacy into models of technological interaction, particularly in contexts involving intelligent systems where user interpretation and trust play critical roles.

Overall, the results emphasize that the successful adoption and evaluation of artificial intelligence technologies depend on a dynamic interaction between system capabilities and human cognitive perceptions. Artificial intelligence can enhance technological experiences, but its impact becomes most evident when users possess the confidence and competence necessary to engage effectively with intelligent systems.

CONCLUSION

The purpose of this study was to examine the structural relationships between artificial intelligence interaction, technology usage, computer self-efficacy, and user satisfaction through a structural equation modeling approach using PLS-SEM. The results demonstrate that the proposed model provides a consistent explanation of how technological interaction and psychological perceptions interact to shape user experiences within intelligent digital environments.

The findings indicate that artificial intelligence plays a significant role in stimulating technology usage. Intelligent systems encourage users to engage more frequently with digital platforms by offering adaptive functionalities, automated processes, and personalized services that enhance efficiency and usability. As users increase their interaction with these technologies, they gain experience and familiarity with digital tools, which contributes to the development of technological competence.

Technology usage was found to significantly influence computer self-efficacy. Continuous interaction with technological systems allows individuals to develop practical skills and confidence in their ability to perform digital tasks. This process reinforces perceptions of technological control and reduces uncertainty when users encounter complex technological environments, particularly those involving artificial intelligence.

Computer self-efficacy emerged as the most influential factor in predicting user satisfaction. Individuals who perceive themselves as capable of effectively using technological systems tend to experience more positive interactions with digital platforms. Higher levels of perceived competence reduce cognitive effort and technological anxiety, allowing users to focus on the functional benefits and value provided by intelligent systems. The structural model also reveals that computer self-efficacy functions as a key mediating mechanism between artificial intelligence interaction and user satisfaction. Artificial intelligence indirectly influences satisfaction by

DOI: 10.46121/pspc.54.1.40

encouraging technological engagement and strengthening perceptions of personal capability. This result suggests that the effectiveness of intelligent technologies depends not only on system performance but also on the degree to which users feel confident in their ability to interact with such systems.

From a practical perspective, the results highlight the importance of promoting digital competencies and technological literacy among users. Organizations and institutions that implement artificial intelligence technologies should complement technological innovation with training programs, user support mechanisms, and interface designs that facilitate learning and reduce complexity. Strengthening users' technological confidence can improve satisfaction and promote sustained adoption of intelligent systems.

From a theoretical perspective, the study contributes to the understanding of technology adoption by integrating psychological constructs with emerging technological contexts. The results confirm that perceptions of technological capability are essential for explaining user responses to artificial intelligence systems and for understanding the dynamics of interaction between humans and intelligent technologies.

In summary, the findings demonstrate that the integration of artificial intelligence into digital environments influences user experiences through a sequence of behavioral and cognitive processes involving technological engagement and perceived competence. Artificial intelligence technologies can enhance satisfaction and technological performance when users possess the skills and confidence necessary to interact effectively with intelligent systems.

REFERENCES

1. J. F. Hair, G. T. M. Hult, C. Ringle, and M. Sarstedt, *A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM)*, 3rd ed. Thousand Oaks, CA: Sage, 2022. https://doi.org/10.4135/9781483377445
2. V. Venkatesh, J. Y. L. Thong, and X. Xu, "Consumer acceptance and use of information technology: Extending the unified theory," *MIS Quarterly*, vol. 36, no. 1, pp. 157–178, 2012. https://doi.org/10.2307/41410412
3. D. Compeau and C. Higgins, "Computer self-efficacy: Development of a measure and initial test," *MIS Quarterly*, vol. 19, no. 2, pp. 189–211, 1995. https://doi.org/10.2307/249688
4. A. Bandura, *Self-Efficacy: The Exercise of Control*. New York, NY: Freeman, 1997. https://doi.org/10.4324/9781315800820
5. B. Shneiderman, "Human-centered artificial intelligence: Reliable, safe and trustworthy," *International Journal of Human-Computer Interaction*, vol. 36, no. 6, pp. 495–504, 2020. https://doi.org/10.1080/10447318.2020.1741118
6. R. Parasuraman and V. Riley, "Humans and automation: Use, misuse, disuse, abuse," *Human Factors*, vol. 39, no. 2, pp. 230–253, 1997. https://doi.org/10.1518/001872097778543886
7. F. D. Davis, "Perceived usefulness, perceived ease of use, and user acceptance of information technology," *MIS Quarterly*, vol. 13, no. 3, pp. 319–340, 1989. https://doi.org/10.2307/249008
8. P. A. Pavlou, "Consumer acceptance of electronic commerce: Integrating trust and risk," *International Journal of Electronic Commerce*, vol. 7, no. 3, pp. 101–134, 2003. https://doi.org/10.1080/10864415.2003.11044275
9. H. Lee and Y. See, "Trust in automation: Designing for appropriate reliance," *Human Factors*, vol. 46, no. 1, pp. 50–80, 2004. https://doi.org/10.1518/hfes.46.1.50.30392
10. A. Rai, "Explainable AI: From black box to glass box," *Journal of the Academy of Marketing Science*, vol. 48, pp. 137–141, 2020. https://doi.org/10.1007/s11747-019-00710-5
11. C. Ringle, S. Wende, and J. Becker, "SmartPLS 4," SmartPLS GmbH, 2022. https://doi.org/10.5281/zenodo.6472517

12. J. Henseler, C. Ringle, and R. Sinkovics, “The use of partial least squares path modeling in international marketing,” *Advances in International Marketing*, vol. 20, pp. 277–319, 2009. https://doi.org/10.1108/S1474-7979(2009)0000020014
13. J. Henseler, C. M. Ringle, and M. Sarstedt, “A new criterion for assessing discriminant validity in variance-based structural equation modeling,” *Journal of the Academy of Marketing Science*, vol. 43, pp. 115–135, 2015. https://doi.org/10.1007/s11747-014-0403-8
14. M. Sarstedt, J. Hair, J. Cheah, J. Becker, and C. Ringle, “How to specify, estimate, and validate higher-order constructs in PLS-SEM,” *Australasian Marketing Journal*, vol. 27, no. 3, pp. 197–211, 2019. https://doi.org/10.1016/j.ausmj.2019.05.003
15. T. Davenport and R. Ronanki, “Artificial intelligence for the real world,” *Harvard Business Review*, vol. 96, no. 1, pp. 108–116, 2018. https://doi.org/10.2139/ssrn.3233461
16. W. W. Chin, “The partial least squares approach to structural equation modeling,” *Modern Methods for Business Research*, pp. 295–336, 1998. https://doi.org/10.4324/9781410604385
17. J. Hair, M. Sarstedt, C. Ringle, and S. Gudergan, *Advanced Issues in Partial Least Squares Structural Equation Modeling*. Thousand Oaks, CA: Sage, 2018. https://doi.org/10.4135/9781483377391
18. R. Etikan, S. Musa, and R. Alkassim, “Comparison of convenience sampling and purposive sampling,” *American Journal of Theoretical and Applied Statistics*, vol. 5, no. 1, pp. 1–4, 2016. https://doi.org/10.11648/j.ajtas.20160501.11
19. D. Straub, M. Boudreau, and D. Gefen, “Validation guidelines for IS positivist research,” *Communications of the AIS*, vol. 13, pp. 380–427, 2004. https://doi.org/10.17705/1CAIS.01324
20. C. Fornell and D. Larcker, “Evaluating structural equation models with unobservable variables and measurement error,” *Journal of Marketing Research*, vol. 18, no. 1, pp. 39–50, 1981. https://doi.org/10.1177/002224378101800104
21. B. Efron and R. Tibshirani, *An Introduction to the Bootstrap*. New York: Chapman & Hall, 1994. https://doi.org/10.1007/978-1-4899-4541-9
22. L. Floridi et al., “AI4People—An ethical framework for a good AI society,” *Minds and Machines*, vol. 28, pp. 689–707, 2018. https://doi.org/10.1007/s11023-018-9482-5
23. E. Brynjolfsson and A. McAfee, *The Second Machine Age: Work, Progress, and Prosperity in a Time of Brilliant Technologies*. New York: W.W. Norton, 2014. https://doi.org/10.2139/ssrn.2463461
24. S. Marakas, M. Yi, and R. Johnson, “The multilevel and multifaceted character of computer self-efficacy,” *Information Systems Research*, vol. 9, no. 2, pp. 126–163, 1998. https://doi.org/10.1287/isre.9.2.126
25. M. Igbaria and J. Iivari, “The effects of self-efficacy on computer usage,” *Omega*, vol. 23, no. 6, pp. 587–605, 1995. https://doi.org/10.1016/0305-0483(95)00035-6
26. A. Benbasat and H. Barki, “Quo vadis TAM?” *Journal of the Association for Information Systems*, vol. 8, no. 4, pp. 211–218, 2007. https://doi.org/10.17705/1jais.00126
27. M. A. Srite and E. Karahanna, “The role of espoused national cultural values in technology acceptance,” *MIS Quarterly*, vol. 30, no. 3, pp. 679–704, 2006. https://doi.org/10.2307/25148745

28. S. Makridakis, "The forthcoming artificial intelligence revolution," *Foresight*, vol. 19, no. 6, pp. 563–573, 2017. https://doi.org/10.1108/FS-03-2017-0011
29. T. Davenport and J. Kirby, *Only Humans Need Apply: Winners and Losers in the Age of Smart Machines*. New York: Harper Business, 2016. https://doi.org/10.4324/9781315689678
30. A. Tarhini, K. Hone, and X. Liu, "A cross-cultural examination of the impact of social, organizational and individual factors on educational technology acceptance," *British Journal of Educational Technology*, vol. 46, no. 4, pp. 739–755, 2015. https://doi.org/10.1111/bjet.12182

Annex A. Operationalization of Variables
Table A1 presents the operationalization of the constructs included in the structural equation model. Each construct was defined conceptually and operationally through reflective indicators measured using a Likert-type scale.

Table A1. Operationalization of Variables

Construct	Conceptual Definition	Operational Definition	Indicators	Measurement Scale
Artificial Intelligence (AI)	Perception of the usefulness, accessibility, and functionality of artificial intelligence systems in digital environments.	Degree to which users perceive AI tools as effective and supportive in performing technological tasks.	AI1 – Perceived usefulness of AI tools; AI2 – Perceived efficiency of AI systems; AI3 – AI support in task completion; AI4 – Accessibility of AI technologies	5-point Likert scale
Technology Usage (TU)	Frequency and intensity of interaction with digital technologies and intelligent systems.	Level of engagement with digital tools and AI-based platforms during daily activities.	TU1 – Frequency of technology use; TU2 – Interaction with AI platforms; TU3 – Use of intelligent digital services	5-point Likert scale
Computer Self-Efficacy (CSE)	Individual belief in the ability to successfully perform tasks using digital technologies.	Perceived confidence in performing tasks with computers and AI-based systems.	CSE1 – Confidence using digital systems; CSE2 – Ability to solve technological problems; CSE3 – Ability to learn new digital tools; CSE4 – Perceived technological competence	5-point Likert scale
User Satisfaction (US)	Overall evaluation of the experience of interacting with technological systems.	Degree of positive perception regarding the performance and usefulness of digital environments.	US1 – Satisfaction with technological experience; US2 – Positive evaluation of digital systems; US3 – Overall satisfaction with AI technologies	5-point Likert scale

Annex B. Expert Judgment Evaluation
Prior to the empirical estimation of the model, the instrument was evaluated by a panel of expert judges to assess content validity. The evaluation considered the relevance, clarity, and theoretical coherence of each indicator with respect to its corresponding construct.

Table B1. Expert Judgment Evaluation

Indicator	Clarity	Relevance	Theoretical Consistency	Decision
AI1	High	High	High	Accepted
AI2	High	High	High	Accepted
AI3	High	High	High	Accepted

Indicator	Clarity	Relevance	Theoretical Consistency	Decision
AI4	High	High	High	Accepted
TU1	High	High	High	Accepted
TU2	High	High	High	Accepted
TU3	High	High	High	Accepted
CSE1	High	High	High	Accepted
CSE2	High	High	High	Accepted
CSE3	High	High	High	Accepted
CSE4	High	High	High	Accepted
US1	High	High	High	Accepted
US2	High	High	High	Accepted
US3	High	High	High	Accepted

The evaluation indicated that all indicators met the required criteria for conceptual clarity, theoretical relevance, and construct representativeness. Therefore, no items were eliminated or modified after the expert review process.

Annex C. Measurement Scales

The following items were used to measure the constructs included in the structural equation model. Respondents evaluated each statement using a five-point Likert scale ranging from 1 (Strongly disagree) to 5 (Strongly agree).

Artificial Intelligence Scale (AI)

Code	Item
AI1	Artificial intelligence tools improve the efficiency of my digital activities.
AI2	AI systems help me complete technological tasks more effectively.
AI3	I find artificial intelligence technologies useful in my daily digital activities.
AI4	AI tools are accessible and easy to integrate into my digital routines.

Technology Usage Scale (TU)

Code	Item
TU1	I frequently use digital technologies in my daily activities.
TU2	I regularly interact with platforms that incorporate artificial intelligence.
TU3	I use intelligent digital services to support my tasks and decisions.

Computer Self-Efficacy Scale (CSE)

Code	Item
CSE1	I feel confident in my ability to use digital technologies effectively.
CSE2	I can solve most technological problems when they occur.
CSE3	I can learn to use new digital tools without much difficulty.
CSE4	I believe I have the skills necessary to use advanced technological systems.

User Satisfaction Scale (US)

Code	Item
US1	I am satisfied with my experience using digital technologies.
US2	My interaction with intelligent technological systems has been positive.
US3	Overall, I am satisfied with the performance of AI-based digital platforms.

DOI: 10.46121/pspc.54.1.40