

Understanding Performance and Effort Expectancy in Generative AI Use through Data Mining Models

Mohamad Noorman Masrek^{1, *}, Abdi Mubarak Syam², Mohd Yusof Mustaffar¹

¹Faculty of Information Science, Universiti Teknologi MARA Selangor Branch, 40150 Shah Alam, Selangor, Malaysia

²Fakultas Ilmu Sosial, Universitas Islam Negeri Sumatera Utara, Sumatera, Indonesia

Corresponding Authors' Email Address: mnoorman@uitm.edu.my

ARTICLE INFO

Article history:

Received: 7 November 2025

Revised: 6 January 2026

Accepted: 16 January 2026

Online first

Published: 10 April 2026

Keywords:

Generative artificial intelligence

Performance expectancy

Effort expectancy

Technology acceptance

UTAUT

<https://doi.org/10.24191/n1z23h53>

ABSTRACT

This study examines how Generative Artificial Intelligence (AI) utilization predicts users' Performance Expectancy and Effort Expectancy within the Unified Theory of Acceptance and Use of Technology (UTAUT) framework. Using data from 480 Indonesian university students, the research employed data mining models in Orange to classify expectancy perceptions based on generative AI usage. Seven algorithms were tested, with Naïve Bayes achieving the highest predictive accuracy. Results indicate that generative AI use moderately predicts both performance and effort expectancy, suggesting that frequent interaction enhances users' perceptions of effectiveness and ease. The findings extend UTAUT into a post-adoption context, confirming that expectancy beliefs evolve through experiential learning. Practically, the study emphasizes the importance of exposure and guided practice in fostering AI familiarity among students. Future research should expand across user groups and explore other generative AI modalities beyond text-based applications.

INTRODUCTION

The rise of Generative Artificial Intelligence (GenAI) tools such as ChatGPT, DALL·E, and Copilot has reshaped how individuals create, communicate, and perform cognitive tasks. These tools represent a transformative technological advancement that automates reasoning processes, enhances creativity, and accelerates productivity across multiple sectors. As GenAI continues to diffuse into education, business, and everyday workflows, understanding how users perceive and evaluate these tools has become a critical area of study (Masrek, Heriyanto & Hussain, 2026).

Recent studies have highlighted the growing role of artificial intelligence technologies in transforming educational practices and learning environments. For instance, Lampropoulos & Papadakis (2025) note that AI-enabled educational technologies have the potential to support personalized learning experiences, increase student engagement, and improve academic performance by adapting to learners' individual needs and characteristics. At the same time, the integration of AI tools into academic environments has also raised important concerns regarding their appropriate use. Zacharis & Papadakis (2025) emphasize that while generative AI can provide valuable support in areas such as formative feedback and administrative assistance, issues related to fairness, reliability, and academic integrity remain important considerations, particularly in assessment contexts.

Despite the rapid diffusion of GenAI technologies (Masrek & Khan, 2025), understanding how users evaluate the usefulness and ease of use of these tools remains essential for explaining their sustained adoption. Within the Unified Theory of Acceptance and Use of Technology (UTAUT), performance expectancy (PE) and effort expectancy (EE) are two core constructs that explain how users perceive the benefits and usability of emerging technologies (Venkatesh et al., 2003). These constructs remain particularly relevant in the context of GenAI systems, where users must assess not only the productivity gains offered by the technology but also the effort required to effectively interact with and integrate these tools into their workflows.

According to the UTAUT model, PE refers to the degree to which an individual believes that using a system will help them achieve gains in task performance, whereas EE refers to the perceived ease associated with using the system (Venkatesh et al., 2003). These two beliefs jointly shape users' behavioral intentions and subsequent technology use. However, much of the existing UTAUT research has been conducted in pre-adoption contexts, emphasizing how expectations influence the intention to use technology. As GenAI technologies mature and become integrated into daily academic and professional practices, it becomes increasingly important to explore the post-adoption phase—that is, how actual use of GenAI shapes users' perceptions of performance and effort over time.

This perspective is consistent with Expectation Confirmation Theory (ECT) (Bhattacharjee, 2001), which posits that users' continued use of technology depends on whether their experiences confirm or disconfirm prior expectations. In the context of GenAI, this means that repeated interaction with AI tools may reinforce users' beliefs about their effectiveness (i.e. PE) and ease of operation (i.e. EE). Examining these relationships can provide insights into the dynamic feedback loop between use and perception—an area that remains underexplored in GenAI adoption research.

Despite growing scholarly interest in AI acceptance, most studies continue to employ traditional survey analysis or structural equation modeling (SEM) to examine theoretical relationships (e.g., Du & Lv, 2024; Kim, Blazquez, & Oh, 2024). While these approaches are effective in identifying associations among constructs, they are often limited in their ability to capture the complex and nonlinear interactions that may exist among behavioral and perceptual factors. Data mining techniques offer a predictive and exploratory alternative, enabling the discovery of hidden patterns and the assessment of model performance using large datasets. Accordingly, this study aims to address three key research questions: (RQ1) Does GenAI

utilization predict PE among users? (RQ2) Does GenAI utilization predict EE among users? And (RQ3) Which data mining model provides the most accurate prediction for each construct? By integrating the UTAUT framework with data mining approaches, this study contributes to both theoretical advancement and methodological innovation in AI adoption research. The findings are expected to enhance understanding of how GenAI usage reinforces user perceptions of performance and effort, thereby informing future system design, user training, and technology acceptance strategies in higher education and beyond.

LITERATURE REVIEW

Unified Theory of Acceptance and Use of Technology (UTAUT)

The Unified Theory of Acceptance and Use of Technology (UTAUT), proposed by Venkatesh et al. (2003), integrates elements from several earlier models of technology acceptance, including the Technology Acceptance Model (TAM) (Davis, 1989), Theory of Planned Behavior (TPB) (Ajzen, 1991), and Innovation Diffusion Theory (IDT) (Rogers, 2003). UTAUT identifies four primary constructs that influence behavioral intention and technology use: PE, EE, social influence, and facilitating conditions.

PE and Effort EE are constructs that correspond conceptually to Perceived Usefulness and Perceived Ease of Use in the Technology Acceptance Model (TAM), but extend them to capture broader, task-oriented expectations of technological performance and effort. Whereas TAM focuses primarily on individual perceptions of usefulness and ease in influencing intention to use (Davis, 1989), UTAUT positions PE and EE within a more comprehensive framework that accounts for behavioral, social, and contextual factors. In the UTAUT model, EE influences PE, as a system perceived to be easy to use is often also perceived as more effective. Together, these perceptions shape behavioral intention, which then predicts actual use. Numerous extensions of the UTAUT model (Venkatesh et al., 2012; Dwivedi et al., 2019) have confirmed that PE and EE are among the most powerful predictors of user acceptance across various technological domains, including e-learning, mobile applications, and AI systems.

In the context of GenAI, UTAUT provides a valuable theoretical lens for understanding user engagement (Venkatesh, 2022). As users interact with tools like ChatGPT, DALL·E, and Copilot, their PE (e.g., the belief that these tools enhance productivity and creativity) and EE (e.g., the perception that the tools are intuitive and easy to use) are central to sustained adoption. However, most existing studies treat these constructs as antecedents of use intention rather than as outcomes shaped by actual usage experience (e.g. Zhang & Wareewanich, 2024; Xia & Yen, 2025). The UTAUT model has been extensively tested across diverse technologies, user groups, and contexts, consistently demonstrating its robustness and predictive validity. Because of this strong empirical foundation, UTAUT-based studies often yield predictable results regarding the influence of PE and EE on behavioral intentions. However, such consistency may also limit theoretical innovation, as it overlooks the post-adoption dynamics through which actual technology use reshapes user perceptions (Thong, Hong & Tam, 2006). Therefore, the present study moves beyond predicting the influence of PE and EE on the intention to adopt GenAI. Instead, it reverses the traditional direction of analysis to examine how real-world GenAI utilization influences users'

performance and effort expectancies, offering a fresh perspective on the evolving nature of technology acceptance.

Post Adoption and Expectation and Confirmation Perspectives

While UTAUT effectively explains technology acceptance during initial adoption stages, it is less explicit about how user perceptions evolve after technology adoption. To address this limitation, researchers often integrate UTAUT with the Expectation Confirmation Theory (ECT) (Bhattacharjee, 2001). ECT posits that users form expectations about a system before use, and upon actual experience, they evaluate whether those expectations are confirmed. If the experience meets or exceeds expectations, users report confirmation and higher satisfaction, reinforcing continued intention to use the technology.

Applied to GenAI, this means that actual AI utilization may reinforce or modify users' performance and effort expectancies. For instance, after using GenAI for tasks such as writing, analysis, or ideation, users may realize its value in enhancing efficiency and quality, thereby reporting higher PE. Similarly, with continued exposure, users may find the technology easier to operate, reducing perceived effort and increasing confidence—thereby enhancing EE. Therefore, analyzing the directional relationship GenAI Utilization → PE and EE provides critical insight into post-adoption learning and cognitive adaptation. This aligns with the growing body of information systems research that combines UTAUT and ECT (e.g. Zuiderwijk & Cligge, 2016), suggesting that users' expectancies evolve dynamically based on direct interaction and perceived confirmation of benefits. Consequently, the present study adopts a post-adoption perspective to model how GenAI use predicts and reinforces these two key constructs.

Importantly, the relationship examined in this study should not be interpreted as a simple circular association in which users evaluate a technology positively merely because they use it. Rather, in the context of emerging technologies such as GenAI, many users begin interacting with the technology without fully understanding its capabilities, limitations, or optimal ways of using it (Bo et al., 2025; Chan, 2025). Through repeated interaction, users gradually learn how to formulate effective prompts, identify suitable tasks for AI assistance, and recognize the boundaries of the technology (Mzwri & Turesányi-Szabo, 2025). This experiential learning process enables users to reassess their beliefs about the system's usefulness and usability based on concrete experience rather than initial expectations.

From this perspective, actual utilization acts as a mechanism of cognitive updating, through which users refine their performance and effort expectations as they accumulate practical experience with the technology. In rapidly evolving tools such as GenAI, users often discover functionalities that were not anticipated prior to use, which may lead to revised perceptions of efficiency gains or ease of interaction. Examining how utilization predicts PE and EE therefore provides insight into the dynamic evolution of user beliefs during the post-adoption phase, extending traditional UTAUT research that primarily focuses on the determinants of initial technology acceptance.

GenAI and User Expectancies

GenAI encompasses technologies capable of autonomously creating text, images, audio, code, and other content through machine learning models such as GPT and diffusion networks (Solanki

& Khublani, 2024). Its widespread adoption across academia, business, and creative industries has spurred new inquiries into how users perceive these tools in terms of their effectiveness and usability (Bi, 2023; El-Habibi et al., 2024; Mittal et al., 2024). Empirical evidence suggests that PE toward GenAI is strongly linked to users' perceptions of improved efficiency, creativity, and academic performance. In contrast, EE is associated with the ease of understanding, learning, and operating these tools (Dwivedi et al., 2023; Le et al., 2024). Despite this emerging interest, limited research has examined how actual usage predicts or modifies these perceptions. Understanding this linkage is crucial because expectancies evolve through experiential feedback—the more users interact with AI, the more they refine their judgments about its value and usability (Palwe & Kumar, 2025). In educational contexts, where GenAI is frequently used for content generation and idea exploration, studying these expectancies provides meaningful insights into how exposure and familiarity contribute to acceptance and continued use (Shen et al., 2025).

Furthermore, the relationship between actual GenAI use and expectancy constructs is particularly relevant in educational environments where technology adoption often occurs through trial, experimentation, and iterative refinement of practices rather than through formal system implementation (Lodge, de Barba & Broadbent, 2024). Students and educators frequently explore generative AI tools to support activities such as brainstorming, drafting written material, summarizing information, or generating alternative perspectives on a topic (Contractor & Reyes, 2025). Through these interactions, users are able to evaluate the practical outcomes of using GenAI within their own academic workflows. Such evaluations may either reinforce or recalibrate their perceptions regarding the extent to which the technology improves task performance or simplifies task execution. Examining how GenAI utilization relates to PE and EE therefore helps illuminate how users translate concrete interaction experiences into broader evaluative judgments about the technology's usefulness and usability, thereby offering a more nuanced understanding of expectancy formation in real-world learning contexts (Kinskofer & Tulis, 2025).

Data Mining Approached in Behavioral Research

Data mining involves uncovering patterns and relationships in large datasets using computational algorithms. In behavioral and technology acceptance research, data mining offers a predictive and exploratory alternative to conventional statistical models such as regression or structural equation modeling (SEM). Rather than focusing on linear relationships or hypothesis testing, data mining emphasizes model performance—how accurately a set of predictors can classify or predict an outcome.

Commonly used data mining algorithms include Decision Trees, Random Forests, k-Nearest Neighbors (kNN), Naïve Bayes, Support Vector Machines (SVM), Neural Networks, and Logistic Regression. These algorithms have been widely applied in behavioral and social science research to uncover patterns and predict human decision-making outcomes. For instance, Decision Tree models have been used to identify treatment-seeking behaviors among cancer patients, demonstrating their interpretability in explaining health-related choices (Oh & Park, 2004). Random Forest algorithms have effectively predicted consumer behavior by analyzing complex and nonlinear relationships in user data (Valecha et al., 2018). Similarly, the k-Nearest Neighbors (kNN) approach has been applied to classify smartphone addiction levels based on behavioral patterns (Wayahdi & Ruziq, 2025). In addition, Naïve Bayes classifiers have been employed to model human behavioral tendencies in smartphone usage (Talha et al., 2020), while Support

Vector Machines (SVM) have proven useful in survey-based behavioral analysis, offering robust classification even with limited or noisy data (Kirchner & Signorino, 2018). Neural Networks have also gained traction in behavioral and attitudinal studies due to their ability to capture complex, nonlinear relationships among psychological variables (Eck, 2018). Finally, Logistic Regression, one of the earliest predictive models, remains a cornerstone in behavioral prediction and survey analysis because of its interpretability and statistical robustness (Roberts et al., 1987). Collectively, these methods provide diverse analytical perspectives that enhance the predictive capacity of behavioral research, making them well-suited for modeling how Generative AI utilization influences constructs such as PE and EE. The performance of each data mining model can be evaluated using six standard classification metrics: Area Under the ROC Curve (AUC), Classification Accuracy (CA), F1-score, Precision, Recall, and the Matthews Correlation Coefficient (MCC). The AUC measures the model's ability to discriminate between classes across all possible thresholds, representing the probability that a randomly selected positive case is ranked higher than a negative one. AUC values between 0.70–0.80 indicate fair discrimination, 0.80–0.90 reflect good discrimination, and values exceeding 0.90 are considered excellent (Fawcett, 2006). Classification Accuracy (CA), the most intuitive metric, quantifies the proportion of correctly predicted cases—both true positives and true negatives—relative to all predictions. An accuracy score above 0.70 is generally deemed acceptable, while values above 0.90 indicate high performance (Alpaydin, 2020).

The F1-score, calculated as the harmonic mean of Precision and Recall, provides a balanced evaluation of a model's ability to minimize both false positives and false negatives, particularly under imbalanced data conditions. An F1 value above 0.70 suggests substantial performance, while scores exceeding 0.80 indicate strong predictive capability (Van Rijsbergen, 1979). Precision measures the model's exactness—the proportion of correctly predicted positive cases among all positive predictions—where values above 0.70 denote high reliability (Ting, 2010). Conversely, Recall, also known as Sensitivity, measures the model's completeness by capturing the proportion of actual positives correctly identified. A recall value above 0.70 indicates satisfactory coverage (Powers, 2011). Finally, the Matthews Correlation Coefficient (MCC) serves as a comprehensive indicator of binary classification performance by incorporating all four elements of the confusion matrix. MCC values greater than 0.30 are interpreted as moderate correlations, while values exceeding 0.60 reflect strong and balanced classification quality (Matthews, 1975).

Conceptual Framework

Grounded in the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003) and informed by the Expectation Confirmation Theory (ECT) (Bhattacharjee, 2001), this study adopts a post-adoption predictive framework. As illustrated in Figure 1 it positions GenAI Utilization as an independent variable influencing users' PE and EE.

Prior research on technology acceptance provides mixed evidence regarding how technology use predicts user perceptions of performance and effort. Kingston (2025) examined the relationship between GenAI utilization and the core Technology Acceptance Model constructs—perceived usefulness and perceived ease of use—among healthcare finance professionals. Although the hypothesized relationships were statistically insignificant, the author suggested that

the limited sample size ($n = 73$) may have reduced statistical power, potentially masking meaningful effects. Despite the nonsignificant findings, Kingston's study underscores the theoretical relevance of investigating how actual use of GenAI relates to users' performance and effort perceptions, particularly in professional and academic contexts where exposure and experience vary widely.

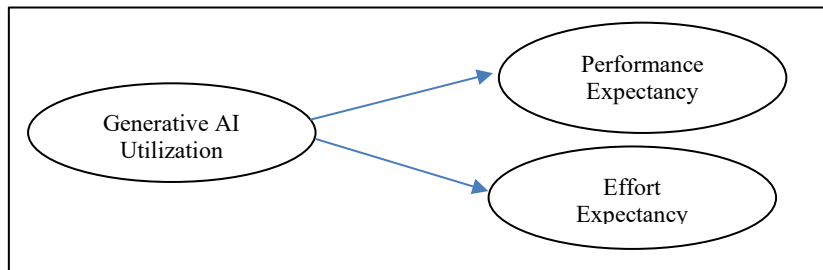


Figure 1. The Conceptual Framework

In contrast, Alismaiel, Cifuentes-Faura & Al-Rahmi (2022) found a significant positive relationship between technology utilization and user perceptions in the context of social media for collaborative learning. Their results indicated that engaging with social media platforms directly enhanced both perceived usefulness and perceived ease of use, ultimately fostering higher levels of student engagement and collaboration. This finding supports the idea that increased interaction with digital technologies can strengthen users' cognitive appraisals of their performance benefits and usability.

Together, these studies provide a theoretical and empirical foundation for the current investigation. While Kingston's (2025) study highlights the need for further empirical testing in the GenAI domain, Alismaiel et al. (2022) demonstrate that technology utilization can positively influence performance- and effort-related perceptions when sufficient user engagement and experience are present. Extending this reasoning, the present study posits that the use of GenAI tools—through repeated exposure, learning, and task integration—will enhance users' PE (belief in the technology's effectiveness) and EE (belief in the technology's ease of use). To this effect, the following hypotheses are proposed:

H1: GenAI utilization significantly predicts PE among users.

H2: GenAI utilization significantly predicts EE among users.

This conceptualization reflects the view that actual engagement with GenAI tools provides experiential feedback that confirms or reshapes users' initial expectations. By applying data mining models to predict these outcomes, the study bridges behavioral theory and computational analytics, offering a novel hybrid methodology for understanding how users' perceptions evolve through real-world AI interaction.

RESEARCH METHODOLOGY

This study employed a quantitative, predictive research design using a data mining approach to examine the influence of GenAI utilization on users' PE and EE. The objective was to identify and compare predictive patterns using multiple classification algorithms implemented in Orange Data Mining software (Demšar et al., 2013). This approach integrates the explanatory power of behavioral theory with computational modeling, allowing the discovery of nonlinear and complex relationships between variables. The target population of this study consisted of Indonesian university students, a group selected because of their high engagement with digital technologies and increasing reliance on GenAI tools for learning, writing, and creative activities. As there was no available sampling frame of AI users at universities, the study adopted a purposive sampling technique. This non-probability method enabled the researcher to intentionally reach students who were aware of or had used GenAI tools such as ChatGPT, Copilot, or DALL·E. A total of 480 valid responses were collected and used for analysis after data cleaning. The relatively large sample size satisfies the recommended ratio for data mining and machine learning classification (generally >10 cases per variable), ensuring adequate predictive power. Data were collected using an online questionnaire developed and distributed via SurveyMonkey, an online subscription-based survey platform. The questionnaire consisted of three main parts:

1. Demographic information (age, gender, academic discipline, and study level).
2. GenAI utilization, measured using a binary (Yes/No) response item asking whether participants had ever used generative AI tools.
3. PE and EE adapted from validated items of the UTAUT (Venkatesh et al., 2003). Each construct was measured using multiple statements on a 5-point Likert scale ranging from 1 = *Strongly Disagree* to 5 = *Strongly Agree*.

Before full deployment, the questionnaire was pre-tested for content clarity and structure by two academic experts in technology management. A pilot test involving 30 university students was then conducted to evaluate internal reliability and face validity. The Cronbach's Alpha coefficients for both PE and EE constructs were above 0.70, indicating acceptable internal consistency for subsequent analysis. Minor revisions were made to wording and item order based on pilot feedback. To align the dataset with the binary classification requirements of data mining models, the PE and EE constructs were transformed from continuous Likert-scale mean scores into binary variables. While Likert-scale responses are commonly treated as continuous measures in behavioral research, certain machine learning and classification algorithms require categorical target variables for prediction modeling. Therefore, the recoding procedure was implemented to enable the application of classification techniques within the Orange data mining environment. Following the recommendations of Harpe (2015), the original 5-point Likert scale was recoded to facilitate classification modeling and to create a clearer interpretive distinction between low and high perception levels. Specifically, respondents with mean scores between 3.10 and 5.00 were recoded as 1 (High Perception) while respondents with mean scores between 0.00 and 3.00 were recoded as 0 (Low Perception). This transformation was based on the neutral midpoint (3.0) of the Likert scale, allowing for a clear separation between "agreement" and "non-agreement" categories.

Although dichotomizing continuous variables may reduce variance and potentially obscure subtle differences in responses, such transformations are sometimes applied in classification-oriented studies where the primary objective is to distinguish between broader perception groups rather than estimate fine-grained differences in scale scores (MacCallum et al., 2002). In the present study, the binary coding allowed the implementation of predictive classification algorithms while maintaining an interpretable distinction between respondents who generally perceive GenAI positively and those with lower or neutral perceptions. According to DiStefano, Shi & Morgan (2021) condensing categories may also help address sparsity issues in categorical modeling, leading to more accurate estimation of parameters

The Generative AI Utilization variable was likewise coded as binary: 1 = Yes (uses Generative AI) and 0 = No (does not use Generative AI). The online survey link was distributed through university email lists, student WhatsApp groups, and social media platforms over a four-week period. Participation was voluntary, and respondents were informed about the confidentiality and anonymity of their responses. Only complete responses were retained, resulting in a total of 480 usable datasets for analysis. The dataset was imported into Orange Data Mining software for preprocessing and modelling. The data were randomly split into 70% for training and 30% for testing to evaluate model generalization and predictive performance. As shown in Figure 2 the analysis utilized multiple classification algorithms available in Orange, including: Decision Tree, Random Forest, k-Nearest Neighbors (kNN), Naïve Bayes, Support Vector Machine (SVM), Neural Network and Logistic Regression (Han, Kamber & Pei, 2012).

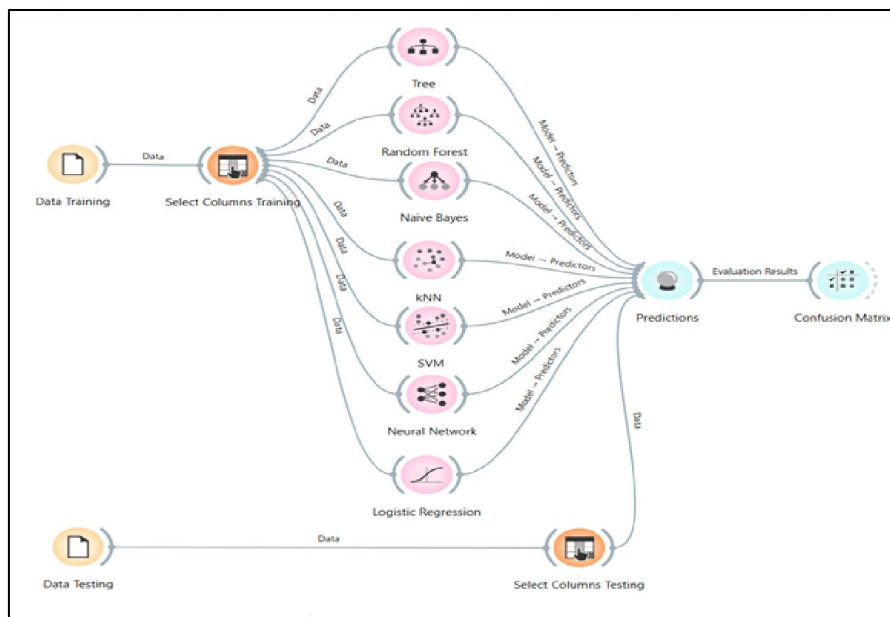


Figure 2. Data analysis procedure

These algorithms were selected because they are suitable for binary outcome prediction and can accommodate both categorical and numerical input features (Kotsiantis, Zaharakis & Pintelas, 2007). Each model was evaluated based on the following performance metrics: Classification

Accuracy (CA), Precision, Recall, F1-score, Area Under the ROC Curve (AUC) and Matthews Correlation Coefficient (MCC). The combination of these metrics provided a comprehensive assessment of model performance, accounting for both classification accuracy and prediction balance across classes. The Orange workflow included the following steps: (i) Data Import and Preprocessing: Cleaning, normalization, and variable selection, (ii) Model Training: Fitting multiple models using 70% of the dataset, (iii) Model Evaluation: Testing on the remaining 30% using cross-validation and (iv) Performance Comparison: Selecting the best-performing model for PU and PEOU prediction based on AUC and F1-score values.

Ethical compliance was ensured throughout the study. All participants were informed about the purpose of the research and provided consent before participation. The survey collected no personal identifiers, and data were stored securely with restricted access. The study adhered to general ethical principles of voluntary participation, anonymity, and confidentiality.

FINDINGS

Demographic Information

A total of 480 Indonesian university students participated in this study. As shown in Table 1, a larger proportion of respondents were female (70.6%), while males accounted for 29.4%. The majority of participants were in the 21–25 age group (55%), representing the typical age range of undergraduate students. Most respondents were single (98%) and enrolled in bachelor's programs (90%), followed by smaller groups from diploma, master's, and doctoral programs. In terms of institutional affiliation, most students were from state or government universities (95%), with only a small representation from private universities and polytechnic/institute settings. Regarding academic background, social sciences and humanities comprised the largest discipline group (52%), followed by business and economics (32%), science and technology (4%), and medical and health sciences (2.5%). This distribution reflects the composition of Indonesian higher education, where social science and business programs dominate student enrollment. The purposive sampling approach ensured inclusion of students who were aware of or had experience using GenAI tools, making them suitable for exploring perceptions of usefulness and ease of use.

Table 1: Demographic Details of Respondents

Variable	Category	Frequency (n)	Percentage (%)
Gender	Male	141	29.4
	Female	339	70.6
Age (years)	Less than 21	24	5.0
	21–25	264	55.0
	26–30	189	39.4
	Above 30	3	0.6
Marital Status	Single	471	98.1
	Married	8	1.7
	Divorced	1	0.2
Program Level	Diploma	13	2.7
	Bachelor	430	89.6
	Master	24	5.0
	Doctoral	13	2.7

Type of University	State / Government	456	95.0
	Private	8	1.7
	Polytechnic / Institute	10	2.1
Field of Study	Social Sciences & Humanities	251	52.3
	Business & Economics	152	31.7
	Science & Technology	20	4.2
	Medical & Health Sciences	12	2.5
	Others	45	9.4

Among the participants, text and writing-based GenAI tools (e.g., ChatGPT, Jasper AI, Copy.ai) were the most commonly used, reported by 95.8% of respondents. These were followed by graphic design tools such as DALL·E and Midjourney (25.2%), and music/audio generation tools like AIVA and Amper Music (16.3%). Smaller proportions of students used GenAI for video or animation creation (11.7%), programming assistance (4.2%), and 3D modeling (2.5%). The dominance of text-based AI applications suggests that students primarily rely on GenAI for academic writing, content creation, and idea development, which aligns with their educational activities and the increasing integration of AI tools in higher learning environments.

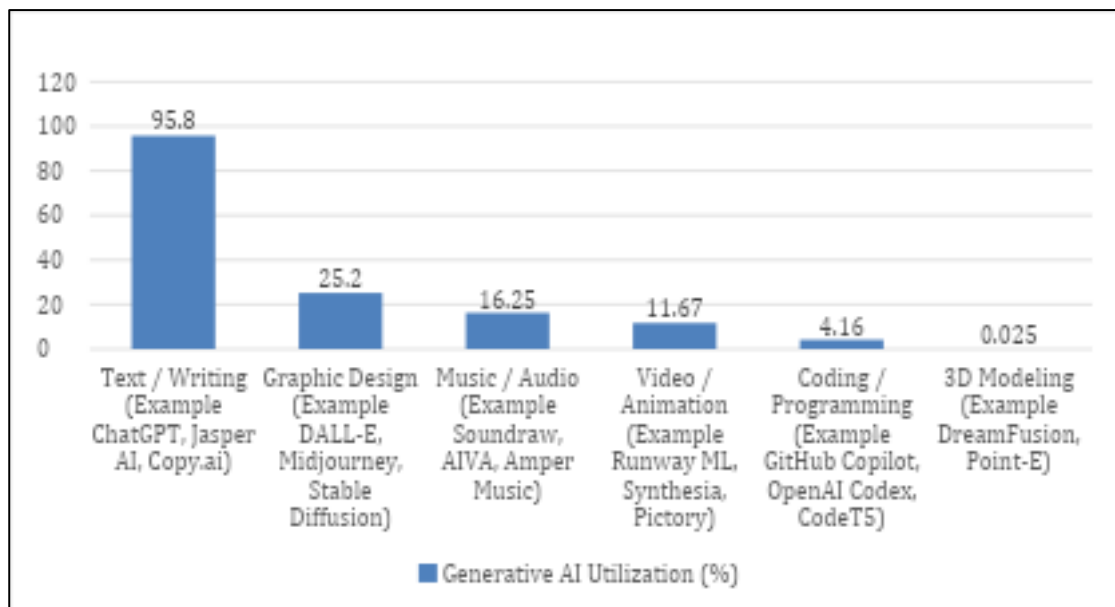


Figure 3: Generative AI Utilization By Respondents

Predicting PE

Table 2 summarizes the predictive performance of six data mining algorithms for estimating PE among Generative AI users. Overall, most models demonstrated acceptable to strong predictive capability based on multiple benchmark metrics, indicating that actual use of generative AI can meaningfully predict users' expectations of performance enhancement. The k-Nearest Neighbors (kNN) model achieved the highest performance across several indices, with AUC = 0.721, CA = 0.861, F1 = 0.840, Precision = 0.832, and Recall = 0.861, all exceeding their

respective benchmark thresholds. Its MCC value of 0.273, while slightly below the 0.30 threshold, still suggests a moderate level of classification correlation between predicted and observed responses. Similarly, the Neural Network and Naïve Bayes models performed strongly, exceeding benchmark levels for F1, Precision, and Recall, reflecting stable and reliable predictive power. Although their AUC scores (0.696 and 0.673) were slightly below the ideal threshold, their MCC values above 0.30 (0.326 and 0.347) demonstrate robust overall classification quality.

In contrast, the Decision Tree, Random Forest, Support Vector Machine (SVM), and Logistic Regression models achieved acceptable Accuracy (CA > 0.70) and F1 (> 0.70) values but fell short of AUC and MCC benchmarks, indicating less discriminative and correlation strength. Despite this, the overall model set produced consistent predictive patterns across metrics, reinforcing the presence of a meaningful relationship between generative AI utilization and perceived task performance. Therefore, Hypothesis H1 is supported, as the data mining results collectively confirm that individuals who engage more actively with generative AI tend to report higher PE. This finding aligns with the post-adoption premise of UTAUT, suggesting that hands-on experience strengthens users' belief in the performance-enhancing potential of emerging technologies.

Table 2: Model Performance for Predicting PE

Model	AUC	CA	F1	Precision	Recall	MCC
Decision Tree	0.500	0.840	0.767	0.740	0.784	0.000
Random Forest	0.703	0.854	0.787	0.804	0.784	0.009
k-Nearest Neighbors (kNN)	0.721	0.861	0.840	0.832	0.861	0.273
Support Vector Machine (SVM)	0.660	0.854	0.787	0.784	0.784	0.000
Neural Network	0.696	0.854	0.840	0.879	0.847	0.326
Naïve Bayes	0.673	0.853	0.854	0.879	0.847	0.347
Logistic Regression	0.703	0.854	0.787	0.784	0.784	0.000
AUC > 0.7 (Fawcett, 2006); CA > 0.7 (Alpaydin (2020)); F1 > 0.7 (Alpaydin (2020)); Precision > 0.7 (Ting, 2010); Recall > 0.7 (Powers, 2011); MCC > 0.3 (Matthews, 1975)						

Predicting EE

The predictive outcomes for EE revealed a consistent performance pattern across the six data mining algorithms, indicating stability and robustness in the models' capacity to classify user perceptions related to the ease of using generative AI. As shown in Table 3, the overall classification accuracy (CA) for all models exceeded the acceptable threshold of 0.70, suggesting that each classifier was capable of producing reliable predictions. However, variations emerged when considering discriminative power and correlation strength.

Among the models, the k-Nearest Neighbors (kNN) algorithm again demonstrated the strongest balance between accuracy and generalization, achieving AUC = 0.712, CA = 0.861, F1 = 0.840, Precision = 0.832, and Recall = 0.861—all exceeding benchmark thresholds. Although its MCC value (0.273) was slightly below the strong correlation threshold, it still reflected moderate predictive alignment between predicted and actual outcomes. The Neural Network and Naïve Bayes models also exhibited comparable performance strength, surpassing benchmark

levels for F1, Precision, and Recall, effectively identifying users with higher perceived ease of use. Both recorded MCC values above 0.30 (0.326 and 0.347, respectively), reinforcing their reliability and generalization capability. By contrast, the Random Forest and Support Vector Machine (SVM) algorithms, while maintaining high overall accuracy (CA > 0.85) and acceptable F1 scores (> 0.78), showed lower AUC and MCC values, indicating limited sensitivity in distinguishing between user categories. The Decision Tree and Logistic Regression models, though yielding solid accuracy, recorded AUC = 0.500 and MCC = 0.000, suggesting near-random classification behavior.

Taken together, these results demonstrate that actual utilization of generative AI significantly predicts EE, thereby supporting Hypothesis H2. The predictive success of models such as kNN, Neural Network, and Naïve Bayes indicates that users who actively engage with generative AI tools tend to perceive them as easier to learn, operate, and integrate into their tasks.

Table 3: Model Performance for Predicting EE

Model	AUC	CA	F1	Precision	Recall	MCC
Decision Tree	0.500	0.840	0.767	0.740	0.784	0.000
Random Forest	0.703	0.854	0.787	0.804	0.784	0.009
k-Nearest Neighbors (kNN)	0.712	0.861	0.840	0.832	0.861	0.273
Support Vector Machine (SVM)	0.649	0.854	0.787	0.784	0.784	0.000
Neural Network	0.696	0.854	0.840	0.879	0.847	0.326
Naïve Bayes	0.673	0.853	0.854	0.879	0.847	0.347
Logistic Regression	0.703	0.854	0.787	0.784	0.784	0.000
AUC > 0.7 (Fawcett, 2006); CA > 0.7 (Alpaydin (2020)); F1 > 0.7 (Alpaydin (2020)); Precision > 0.7 (Ting, 2010); Recall > 0.7 (Powers, 2011); MCC > 0.3 (Matthews, 1975)						

DISCUSSION

Discussion Related to (RQ1): GenAI utilization and PE

The results of this study affirm that GenAI utilization predicts users' PE, providing empirical support for Hypothesis 1 (H1). This finding reinforces the UTAUT proposition that actual engagement with technology enhances perceptions of performance benefits over time (Venkatesh et al., 2003). Users who employ AI tools for tasks such as writing, summarizing, or content generation tend to recognize the tangible improvements these tools bring to productivity and efficiency. This outcome is consistent with the Expectation Confirmation Theory (Bhattacharjee, 2001), which posits that when users' experiences confirm their expectations, satisfaction and positive performance perceptions are strengthened. Hence, the data imply that repeated exposure to GenAI may refine users' understanding of its functional advantages, leading to a more confident belief in its performance-enhancing potential.

Comparatively, these findings differ from Kingston (2025), who reported no significant relationship between AI utilization and perceived usefulness in a small professional sample. The divergence may stem from differences in sample size and context—this study's larger and more diverse dataset (n = 480) and the educational setting may have allowed for a clearer pattern of

experiential reinforcement. Conversely, the results align with Alismaiel, Cifuentes-Faura & Al-Rahmi (2022), who found that technology engagement positively influenced users' perceptions of usefulness and performance within social media-based learning environments. The similarity suggests that across contexts—whether in collaborative learning or AI interaction—consistent use enhances performance-related perceptions. Consequently, the current findings provide fresh evidence that GenAI utilization contributes to post-adoption reinforcement of PE, underscoring the role of experience as a key mechanism driving sustained technology acceptance.

Discussion Related to RQ2: GenAI utilization and EE

The results of this study reveal an important insight: familiarity with GenAI tools cultivates users' perception of ease and comfort in interacting with them, underscoring a clear experiential dimension in EE. Unlike PE—which concerns perceived outcomes and value—EE reflects the learning process and perceived simplicity of the technology interface. The predictive models, particularly Naïve Bayes and Neural Network, consistently showed that those who use GenAI more frequently report higher ease-of-use perceptions. This outcome suggests that EE is not an a priori belief, but an evolving state shaped by continued engagement, experimentation, and cognitive adaptation. In essence, as students gain mastery over the prompts, outputs, and limitations of GenAI systems, the technology becomes progressively less intimidating and more intuitive, reinforcing a sense of usability.

This interpretation highlights the experiential and pedagogical value of exposure in shaping users' perceptions. The finding expands the UTAUT post-adoption narrative (Venkatesh et al., 2003) by showing that ease of use is refined through actual interaction rather than simply anticipated before adoption. The trajectory is consistent with the Expectation Confirmation Theory (Bhattacharjee, 2001)—the more users' real experiences confirm their initial expectations of simplicity, the more confident they become in their ability to use the system effectively. In this way, EE can be viewed as a learning outcome, built through incremental reductions in cognitive load and uncertainty.

When compared with previous research, the findings reveal both contrast and convergence. The non-significant outcomes in Kingston (2025) may reflect contextual or experiential limitations: professionals in healthcare finance, often time-constrained, may not have had the iterative exposure required to internalize ease-of-use perceptions. Conversely, Alismaiel, Cifuentes-Faura & Al-Rahmi (2022) found that collaborative learning through social media platforms enhanced students' perceived ease of use, validating the idea that interactive practice fosters technological comfort. The present study extends these observations to GenAI, confirming that repeated and task-oriented interaction—rather than passive awareness—cultivates higher EE. This reinforces the pedagogical implication that active, guided engagement with GenAI tools is essential for developing sustained ease-of-use perceptions, particularly in academic environments where AI literacy is still emerging.

Discussion Related to RQ3: Most accurate prediction data mining model

The comparative analysis of the seven data mining algorithms revealed that Naïve Bayes consistently produced the most balanced and accurate predictions for both constructs—PE and EE—followed closely by Neural Network and k-Nearest Neighbors (kNN) models. This outcome

illustrates the value of probabilistic and nonlinear learning approaches in modeling behavioral constructs that are inherently multidimensional and influenced by both categorical and continuous factors. The strong performance of Naïve Bayes, which assumes conditional independence among predictors, indicates that even with limited feature interdependence, the underlying data patterns were sufficiently distinct to classify users' expectancy levels accurately. Meanwhile, the comparable results from Neural Network and kNN suggest that users' perceptions of GenAI may follow nonlinear trajectories, where subtle variations in usage frequency or context produce significant shifts in perceived effort and performance.

These findings also demonstrate that data mining models can meaningfully complement traditional behavioral analysis techniques such as regression or structural equation modeling (SEM). Unlike SEM, which focuses on causal estimation and path significance, data mining emphasizes pattern recognition and predictive validity. **The ability of models like Naïve Bayes and Neural Networks to predict expectancy constructs with accuracy levels above 85% (CA \approx 0.85) underscores their potential as diagnostic tools for identifying users with differing acceptance profiles.** This methodological insight extends the predictive dimension of UTAUT research, showing how machine learning can operationalize behavioral constructs in a more dynamic, data-driven manner.

CONCLUSION

This study investigated the predictive relationship between GenAI utilization and two core constructs of the UTAUT, PE and EE—using data mining models. The analyses, based on 480 Indonesian university students, revealed three key findings. First, GenAI utilization moderately predicted PE, indicating that students who frequently engaged with AI tools were more likely to perceive them as enhancing their academic performance and productivity. Second, GenAI utilization significantly predicted EE, suggesting that repeated interaction fosters greater ease and familiarity with AI tools. Third, across the seven models tested, the Naïve Bayes algorithm consistently achieved the best predictive performance for both constructs, followed closely by Neural Network and k-Nearest Neighbors (kNN) models. These results collectively support the study's three hypotheses and demonstrate that behavioral perceptions such as performance and EE can be effectively modeled through computational learning approaches.

From a theoretical standpoint, this study contributes to the post-adoption extension of the UTAUT framework. The results affirm that expectancy beliefs are not static precursors of technology use but rather dynamic outcomes shaped through experiential learning and confirmation processes. This finding complements the Expectation Confirmation Theory (ECT) by showing that continued use of GenAI reinforces both perceived performance benefits and ease of interaction. Moreover, the integration of data mining techniques demonstrates that predictive analytics can serve as a powerful complement to traditional behavioral models, capturing nonlinear and complex user-perception dynamics often overlooked in linear statistical approaches. In practical terms, the findings highlight the importance of exposure and guided interaction in building positive user perceptions of GenAI. Universities and educators can leverage this insight by designing curricular interventions, workshops, or practice-based training

that allow students to explore AI tools across different tasks and disciplines. By encouraging active and repeated use, institutions can enhance students' confidence and competence in engaging with AI technologies, ultimately promoting sustained and responsible adoption. The demonstrated predictive capability of models like Naïve Bayes also opens opportunities for developing AI-driven user analytics dashboards that can help educators identify varying levels of student acceptance and tailor support accordingly.

Several limitations should be acknowledged when interpreting these findings. First, the study's sample was restricted to university students in Indonesia, which limits the generalizability of results to other populations such as professionals or older adults. Students may also have distinct digital habits and learning motivations that shape their perceptions differently from workplace users. Second, participants reported using GenAI primarily for text-based activities—such as writing, summarization, and information retrieval—while fewer engaged with other modalities like image, code, or video generation. This usage pattern may have constrained the variability in expectancy perceptions and the scope of the findings. Third, the use of self-reported measures introduces potential response biases, while the binary transformation of variables, though suitable for data mining, may have simplified nuanced perception differences among users.

Future research could extend this study in several directions. First, conducting similar predictive analyses with more diverse populations—including working professionals, educators, and cross-cultural samples—would enhance external validity and broaden the understanding of GenAI acceptance. Second, researchers should examine different domains of AI utilization, such as image, audio, and code generation, to explore whether expectancy perceptions vary by application type or task complexity. Third, integrating longitudinal or behavioral trace data could capture changes in expectancy beliefs over time, providing stronger evidence for post-adoption learning effects. Finally, combining data mining with structural modeling approaches may yield a richer understanding of both the predictive and causal mechanisms underpinning technology acceptance, bridging computational and behavioral paradigms.

ACKNOWLEDGEMENTS

The author gratefully acknowledges the support provided by the Faculty of Information Science, Universiti Teknologi MARA, and the Faculty of Social Sciences, Universitas Sumatera Utara, in facilitating this research. The author also extends sincere appreciation to all respondents for their voluntary participation in the study. This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

REFERENCES

- Ajzen, I. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Processes*, 50(2), 179–211. [https://doi.org/10.1016/0749-5978\(91\)90020-T](https://doi.org/10.1016/0749-5978(91)90020-T)

- Alismaiel, O. A., Cifuentes-Faura, J., & Al-Rahmi, W. M. (2022). Social media technologies used for education: An empirical study on TAM model during the COVID-19 pandemic. *Frontiers in Education*, 7, Article 882831. <https://doi.org/10.3389/educ.2022.882831>
- Alpaydin, E. (2020). *Introduction to machine learning* (4th ed.). MIT Press.
- Bhattacharjee, A. (2001). Understanding information systems continuance: An expectation-confirmation model. *MIS Quarterly*, 25(3), 351–370. <https://doi.org/10.2307/3250921>
- Bi, Q. (2023). Analysis of the application of generative AI in business management. *Advances in Economics and Management Research*, 6(1), 36-36. <https://doi.org/10.56028/aemr.6.1.36.2023>
- Bo, J. Y., Kazemitabaar, M., Zhuang, E., & Anderson, A. (2025). Who's the leader? Analyzing novice workflows in LLM-assisted debugging of machine learning code. *arXiv*. <https://doi.org/10.48550/arxiv.2505.08063>
- Chan, C. K. Y. (2025). AI as the therapist: Student insights on the challenges of using generative AI for school mental health frameworks. *Behavioral Sciences*, 15(3), 287. <https://doi.org/10.3390/bs15030287>
- Contractor, Z., & Reyes, G. (2025). Generative AI in higher education: Evidence from an elite college. *arXiv*. <https://doi.org/10.48550/arxiv.2508.00717>
- Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, 13(3), 319–340. <https://doi.org/10.2307/249008>
- Demšar, J., Curk, T., Erjavec, A., Gorup, Č., Hočevar, T., Milutinović, M., & Zupan, B. (2013). Orange: data mining toolbox in Python. *The Journal of Machine Learning Research*, 14(1), 2349-2353.
- DiStefano C., Shi D., Morgan G. B. (2021). Collapsing categories is often more advantageous than modeling sparse data: Investigations in the CFA framework. *Structural Equation Modeling: A Multidisciplinary Journal*, 28(2), 237–249. <https://doi.org/10.1080/10705511.2020.1803073>
- Du, L., & Lv, B. (2024). Factors influencing students' acceptance and use generative artificial intelligence in elementary education: An expansion of the UTAUT model. *Education and Information Technologies*, 29(18), 24715-24734. <https://doi.org/10.1007/s10639-024-12835-4>
- Dwivedi, Y. K., Hughes, D. L., Baabdullah, A. M., Ribeiro-Navarrete, S., Giannakis, M., Al-Debei, M. M., Dennehy, D., Metri, B., Buhalis, D., Cheung, C. M. K., Conboy, K., Dutot, V., Dwivedi, R., Jebarajakirthy, C., Kim, Y., Krishen, A. S., Kumar, V., Papagiannidis, S., Rana, N. P., ... Wirtz, J. (2023). So what if ChatGPT wrote it? Multidisciplinary perspectives on opportunities, challenges and implications of generative conversational AI for research, practice and policy. *International Journal of Information Management*, 71, 102642. <https://doi.org/10.1016/j.ijinfomgt.2023.102642>
- Dwivedi, Y. K., Rana, N. P., Jeyaraj, A., Clement, M., & Williams, M. D. (2019). Re-examining the unified theory of acceptance and use of technology (UTAUT): Towards a revised theoretical model. *Information Systems Frontiers*, 21(3), 719–734. <https://doi.org/10.1007/s10796-017-9774-y>
- Eck, A. (2018). Neural networks for survey researchers. *Survey Practice*, 11(1). <https://doi.org/10.29115/SP-2018-0002>
- El-Habibi, M. F., Hamed, M. A., Sababa, R. Z., Al-Hanjori, M. M., Abu-Nasser, B. S., & Abu-Naser, S. S. (2024). Generative AI in the creative industries: Revolutionizing art, music, and media. *International Journal of Academic Engineering Research*, 8(10), 71–74
- Fawcett, T. (2006). An introduction to ROC analysis. *Pattern Recognition Letters*, 27(8), 861–874. <https://doi.org/10.1016/j.patrec.2005.10.010>

- Han, J., Kamber, M., & Pei, J. (2012). *Data mining: Concepts and techniques*. Morgan Kaufmann Publishers.
- Harpe, S. E. (2015). How to analyze Likert and other rating scale data. *Currents in Pharmacy Teaching and Learning*, 7(6), 836–850. <https://doi.org/10.1016/j.cptl.2015.08.001>
- Kim, Y., Blazquez, V., & Oh, T. (2024). Determinants of generative AI system adoption and usage behavior in Korean companies: Applying the UTAUT model. *Behavioral Sciences*, 14(11), 1035.
- Kingston, K. R. (2025). *AI usage as a predictor of technology acceptance among healthcare finance professionals* [Doctoral dissertation, Grand Canyon University]. Grand Canyon University Repository.
- Kinskofer, F., & Tulis, M. (2025). Motivational and appraisal factors shaping generative AI use and intention in Austrian higher education students and teachers. *Frontiers in Education*, 10, 1677827. <https://doi.org/10.3389/educ.2025.1677827>
- Kirchner, A., & Signorino, C. S. (2018). Using support vector machines for survey research. *Survey Practice*, 11(1). <https://doi.org/10.29115/SP-2018-0001>
- Kotsiantis, S. B., Zaharakis, I., & Pintelas, P. (2007). Supervised machine learning: A review of classification techniques. *Emerging artificial intelligence applications in computer engineering*, 160(1), 3-24.
- Lampropoulos, G., & Papadakis, S. (2025). The educational value of artificial intelligence and social robots. In G. Lampropoulos & S. Papadakis (Eds.), *Social robots in education* (Studies in Computational Intelligence, Vol. 1194). https://doi.org/10.1007/978-3-031-82915-4_1
- Le, V. H., Nguyen, H., Vo-Thanh, T., Nguyen, H. T. T., & Tran, T. T. D. (2024). Generative AI, why, how, and outcomes: A user perspective. *AIS-Transactions on Human-Computer Interaction*, 16(1). <https://aisel.aisnet.org/thci/vol16/iss1/1/>
- Lodge, J. M., de Barba, P., & Broadbent, J. (2024). The rise of generative AI and the crisis of confidence in assessment: A regulation perspective. *Computers and Education: Artificial Intelligence*, 6, 100189. <https://doi.org/10.1016/j.caeai.2023.100189>
- MacCallum, R. C., Zhang, S., Preacher, K. J., & Rucker, D. D. (2002). On the practice of dichotomization of quantitative variables. *Psychological Methods*, 7(1), 19–40. <https://doi.org/10.1037/1082-989X.7.1.19>
- Masrek, M. N., Heriyanto, H., & Hussain, A. (2026). Ethical decision making and astute use of artificial intelligence. *Edelweiss Applied Science and Technology*, 10(1), 1163–1176. <https://doi.org/10.55214/2576-8484.v10i1.11868>
- Masrek, M. N., & Khan, M. K. (2025). Exploring AI applications in libraries: A topic modelling analysis of recent trends and themes. *Journal of Islamic, Social, Economics and Development (JISED)*, 10(79), 894–906. <https://doi.org/10.55573/JISED.107970>
- Matthews, B. W. (1975). Comparison of the predicted and observed secondary structure of T4 phage lysozyme. *Biochimica et Biophysica Acta (BBA) – Protein Structure*, 405(2), 442–451. [https://doi.org/10.1016/0005-2795\(75\)90109-9](https://doi.org/10.1016/0005-2795(75)90109-9)
- Mittal, U., Sai, S., Chamola, V., & Sangwan, D. (2024). A comprehensive review on generative AI for education. *IEEE Access*, 12, 142733–142759. <https://doi.org/10.1109/ACCESS.2024.3468368>

- Mzwri, K., & Turcsányi-Szabo, M. (2025). The impact of prompt engineering and a generative AI-driven tool on autonomous learning: A case study. *Education Sciences*, 15(2), 199. <https://doi.org/10.3390/educsci15020199>
- Oh, H. S., & Park, H. A. (2004). Decision tree model of the treatment-seeking behaviors among Korean cancer patients. *Cancer Nursing*, 27(4), 259-266. https://journals.lww.com/cancernursingonline/fulltext/2004/07000/decision_tree_model_of_the_treatment_seeking.1.aspx
- Palwe, R., & Kumar, A. (2025). Redefining usability in the age of generative AI: Towards a new evaluation paradigm. *International Journal of Computer and Artificial Intelligence*, 6(2), 155-163. <https://doi.org/10.33545/27076571.2025.v6.i2b.193>
- Powers, D. M. W. (2011). Evaluation: From precision, recall and F-measure to ROC, informedness, markedness and correlation. *Journal of Machine Learning Technologies*, 2(1), 37–63. <https://doi.org/10.48550/arXiv.2010.16061>
- Roberts, G., Rao, N. K., & Kumar, S. (1987). Logistic regression analysis of sample survey data. *Biometrika*, 74(1), 1-12. <https://doi.org/10.1093/biomet/74.1.1>
- Rogers, E. M. (2003). *Diffusion of innovations* (5th ed.). Free Press.
- Shen, H., Shen, L., Wu, W., & Zhang, K. (2025, April). Ideationweb: Tracking the evolution of design ideas in human-ai co-creation. In *Proceedings of the 2025 CHI Conference on Human Factors in Computing Systems* (pp. 1-19).
- Solanki, S. R., & Khublani, D. K. (2024). Introduction to generative AI. In *Generative Artificial Intelligence: Exploring the Power and Potential of Generative AI* (pp. 1-35). Berkeley, CA: Apress.
- Talha, I. M., Salehin, I., Debnath, S. C., Saifuzzaman, M., Moon, N. N., & Nur, F. N. (2020, July). Human behaviour impact to use of smartphones with the python implementation using naive Bayesian. In *2020 11th International Conference on Computing, Communication and Networking Technologies (ICCCNT)* (pp. 1-6). IEEE.
- Thong, J. Y. L., Hong, S. J., & Tam, K. Y. (2006). The effects of post-adoption beliefs on the expectation-confirmation model for information technology continuance. *International Journal of Human-Computer Studies*, 64(9), 799–810. <https://doi.org/10.1016/j.ijhcs.2006.05.001>
- Ting, K. M. (2010). *Precision and recall*. In C. Sammut & G. I. Webb (Eds.), *Encyclopedia of machine learning* (pp. 781–782). Springer. https://doi.org/10.1007/978-0-387-30164-8_652
- Valecha, H., Varma, A., Khare, I., Sachdeva, A., & Goyal, M. (2018, November). Prediction of consumer behaviour using random forest algorithm. In *2018 5th IEEE Uttar Pradesh section international conference on electrical, electronics and computer engineering (UPCON)* (pp. 1-6). IEEE.
- Van Rijsbergen, C. J. (1979). *Information retrieval* (2nd ed.). Butterworths.
- Venkatesh, V. (2022). Adoption and use of AI tools: a research agenda grounded in UTAUT. *Annals of Operations Research*, 308(1), 641-652. <https://doi.org/10.1007/s10479-020-03918-9>
- Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly*, 27(3), 425–478. <https://doi.org/10.2307/30036540>
- Venkatesh, V., Thong, J. Y. L., & Xu, X. (2012). Consumer acceptance and use of information technology: Extending the unified theory of acceptance and use of technology. *MIS Quarterly*, 36(1), 157–178. <https://doi.org/10.2307/41410412>

- Wayahdi, M. R., & Ruziq, F. (2025). Predicting smartphone addiction levels with k-nearest neighbors using user behavior patterns. *Jurnal Teknik Informatika (Jutif)*, 6(5), 3379-3391. <https://doi.org/10.52436/1.jutif.2025.6.5.4905>
- Xia, Y., & Chen, Y. (2025). Driving factors of generative AI adoption in new product development teams from a UTAUT perspective. *International Journal of Human-Computer Interaction*, 41(10), 6067-6088. <https://doi.org/10.1080/10447318.2024.2375686>
- Zacharis, G., & Papadakis, S. (2025). Can AI grade like a human? Validity, reliability, and fairness in university coursework assessment. *Educational Process: International Journal*, 19, e2025591. <https://doi.org/10.22521/edupij.2025.19.591>
- Zhang, X., & Wareewanich, T. (2024). A study of the factors influencing teachers' willingness to use generative artificial intelligence based on the UTAUT model. *International Journal of Interactive hMobile Technologies*, 18(6). <https://doi.org/10.3991/ijim.v18i06.47991>
- Zuiderwijk, A., & Cligge, M. (2016). The acceptance and use of open data infrastructures—Drawing upon UTAUT and ECT. In *Electronic government and electronic participation* (pp. 91-98). IOS Press.