Journal of Multimedia Trend and Technology - JMTT
Volume 4, Issue 2, August 2025, ISSN 2964-1330
https://journal.educollabs.org/index.php/jmtt/

Understanding GenAI Adoption in Education: A Systematic Literature Review

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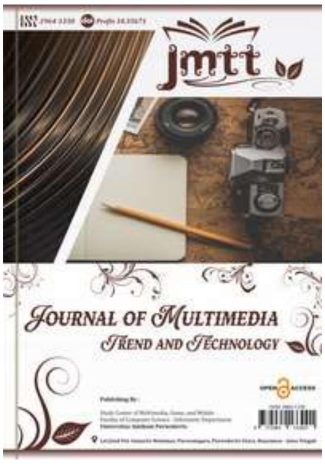
ARTICLE INFO



History :

Submit on 14 Feburary 2025
Review on 7 May 2025
Accepted on 30 July 2025

Keyword :

Generative;
Artificial intelligence;
Technology adoption;
UTAUT;
Education.

ABSTRACT

This study conducts a systematic literature review of 40 peer-reviewed articles to investigate behavioral factors influencing the adoption of Generative Artificial Intelligence (GenAI) in education. Using PRISMA guidelines, the review identifies key constructs from the Unified Theory of Acceptance and Use of Technology (UTAUT) including performance expectancy, effort expectancy, social influence, and facilitating conditions as consistent predictors of GenAI usage. Additionally, complementary variables such as trust, perceived risk, self-efficacy, hedonic motivation, and ethical concerns are found to significantly shape user engagement. The integration of UTAUT with models like TAM, TPB, and SCT enhances explanatory depth, offering a multidimensional framework for understanding GenAI adoption. The study proposes a conceptual model and highlights the importance of inclusive, context-sensitive approaches to support responsible GenAI integration in academic settings.

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INTRODUCTION

Implementation of Generative Artificial Intelligence (GenAI) in global education has demonstrated significant progress in recent years, particularly in enhancing adaptive and personalized teaching and learning processes. Lo [1] affirm that GenAI can positively contribute to learning outcomes especially in conceptual understanding and intermediate-level reasoning skills when its integration is pedagogically designed and accompanied by adequate instructional supervision. These findings are further supported by Deng [2], which when GenAI is utilized as tool for exploration, planning or learning can increase cognitive, emotional, and behavioural engagement. In practice, GenAI is widely employed in classrooms and higher education institutions for formative feedback provision, evaluation instrument design, enrichment of learning materials, and support in writing and programming activities [3]. However, these promising capabilities are still confronted with critical challenges, including the risk of hallucination, algorithmic bias, and the potential decline in critical thinking skills if not supported by appropriate pedagogical design [4]. On the other hand, Wood [5] found that students experience increased confidence, engagement, and comfort when experimenting with the support of GenAI, despite an explicit need for ethical regulation and transparency in its use within assessment contexts. Overall, the landscape of GenAI implementation in global education indicates substantial opportunities to enhance learning quality, provided that its integration is grounded in instructional design, authentic assessment, and the strengthening of critical literacy regarding AI technologies.

In Indonesian education, the use of Generative AI has been shown to enhance both efficiency and quality in learning processes. Astrid [6] states that AI assists in developing more adaptive teaching materials, thereby meeting the diverse needs of individual students. AI functions as a learning partner, fostering creativity and increasing student engagement. Learners become more active in educational activities when utilizing AI-based tools. With AI support, the learning experience becomes more inclusive, enabling students from various backgrounds and abilities to gain better access to educational content. Even so, implementation of AI faces a number of challenges and ethical concerns. These include issues related to data privacy and protection, as well as algorithmic bias and discrimination. Use of GenAI by students often perceived as detrimental by lectures and educators. This concern arises form the belief that GenAI diminish students critical thinking, creativity, and independences. For Instance, students relying too much on AI to complete assignments or produce written work rapidly without zero understanding of the material and its authenticity [7]. This phenomenon raises concerns about declining learning quality, emergence of digital plagiarism, and reduced interaction. Moreover, unsupervised use of GenAI poses the risk of creating gaps of understanding, as students who depend entirely on AI may miss opportunities to develop logical reasoning and problem-solving skills independently [8]. Consequently, the presence of GenAI can be viewed as a threat to the role of educators and the fundamental goals of education, which emphasize the development of intellectual capacity and student character.

The emergence of GenAI in educational settings has led to a divide among users in which some embrace it enthusiastically, while others remain skeptical, perceiving its impact on students as largely negative. As previously discussed, GenAI offers positive contributions to learning by encouraging student engagement and serving as a valuable learning partner that supports inquiry and exploration. However, without proper guidance, students may fall into the misconception that AI consistently provides accurate answers. In reality, the effective use of AI in education can directly enhance learning quality when applied appropriately [9]. Therefore, a deeper exploration is needed to identify which factors influence the use of AI in educational context. Thus, this study conducts a systematic literature review on research analyzing user behavior toward GenAI in education context. This research aims to identify and elaborate on the key factors that shape GenAI usage behavior. Furthermore, a conceptual model will be developed to illustrate each influencing factor and its relationship with others. This study will focus on literature grounded in the Unified Theory of Acceptance and Use of Technology (UTAUT), along with its extensions and predecessors. UTAUT is selected due to its comprehensive framework for explaining technology acceptance, as it integrates constructs from eight foundational theories: Theory of Reasoned Action (TRA), Technology Acceptance Model (TAM), Motivational Model (MM), Theory of Planned Behavior (TPB), Combined TAM and TPB (C-TAM-TPB), Model of PC Utilization (MPCU), Innovation Diffusion Theory (IDT), and Social Cognitive Theory (SCT) [10]. This theoretical foundation

allows for a holistic analysis encompassing perspectives from information systems, psychology, and sociology. To achieve these objectives, this study is guided by two research question:
RQ1. What factors can explain user behavior in utilizing GenAI within educational contexts?
RQ2. Which factor significantly influences GenAI usage behavior, and what is the nature of its impact?

METHOD

To facilitate the discussion and design of this project, in the design planning we use the prototyping method. Prototyping is an approach to software or product development that involves creating an early version of a product, called a "prototype", to explore basic ideas, concepts, or functionality before producing a final product. These prototypes typically do not have all the features or level of completion that will be in the final product, but are sufficient to demonstrate the core idea or functionality. The prototype method used has the following stages.

A. Research Design

This study adopts a qualitative research methodology to achieve its objectives. A systematic literature review (SLR) is conducted on selected journal articles to address research questions related to user behavior in the use of GenAI within educational contexts. The review follows the PRISMA guidelines to ensure methodological rigor and transparency. Figure 1 presents the PRISMA flow chart used in this study. This study involves four key stages: Identification, Screening, Eligibility, and Inclusion. In the identification stage, an initial search was conducted by developing a search query and retrieving journal articles from the ScienceDirect database. Several keywords were used and combined using Boolean operators “OR” and “AND” to generate relevant search results. The keywords used are presented in Table 1. The initial search yielded 5043 articles that could potentially serve as references for this study.

Table 1. Search Keyword

First Keyword	Second Keyword	Third Keyword
“Chatbot” OR “GPT	“Adoption” OR “Intention” OR “Acceptance”	“Academic” OR “Education”

In the screening stage, articles were filtered using several criteria, including “the article must be written in English, published between 2021 and 2025, and must apply the UTAUT theory or its constructs”. This process resulted in 666 articles considered potentially relevant for this study. In the eligibility stage, the titles and abstracts of these 666 articles were reviewed using inclusion and exclusion criteria, as presented in Table 2 These criteria focused on selecting articles that analyse AI adoption or user behaviour in educational contexts, apply the UTAUT theory (including its constructs and predecessors), and use appropriate methodologies. Studies employing systematic literature reviews or similar approaches were excluded from the article pool. Additionally, research that does not focus on academic or educational settings, or merely mentions AI/UTAUT without in-depth analysis, was also excluded.

Table 2. Inclusion and Exclusion Criteria

Inclusion	Exclusion
Article comes from peer-reviewed research journal	Article must be in English
Article must come from Scopus indexed Journals	Article must be available online
Article is published in between 2021-2025	Article must focuses on generative AI use in academic context
	Article must use SEM Methodologies (PLS SEM/CB SEM)

Finally, in the inclusion stage, the final set of articles for review was determined. To minimize potential bias, four researchers independently selected the articles and engaged

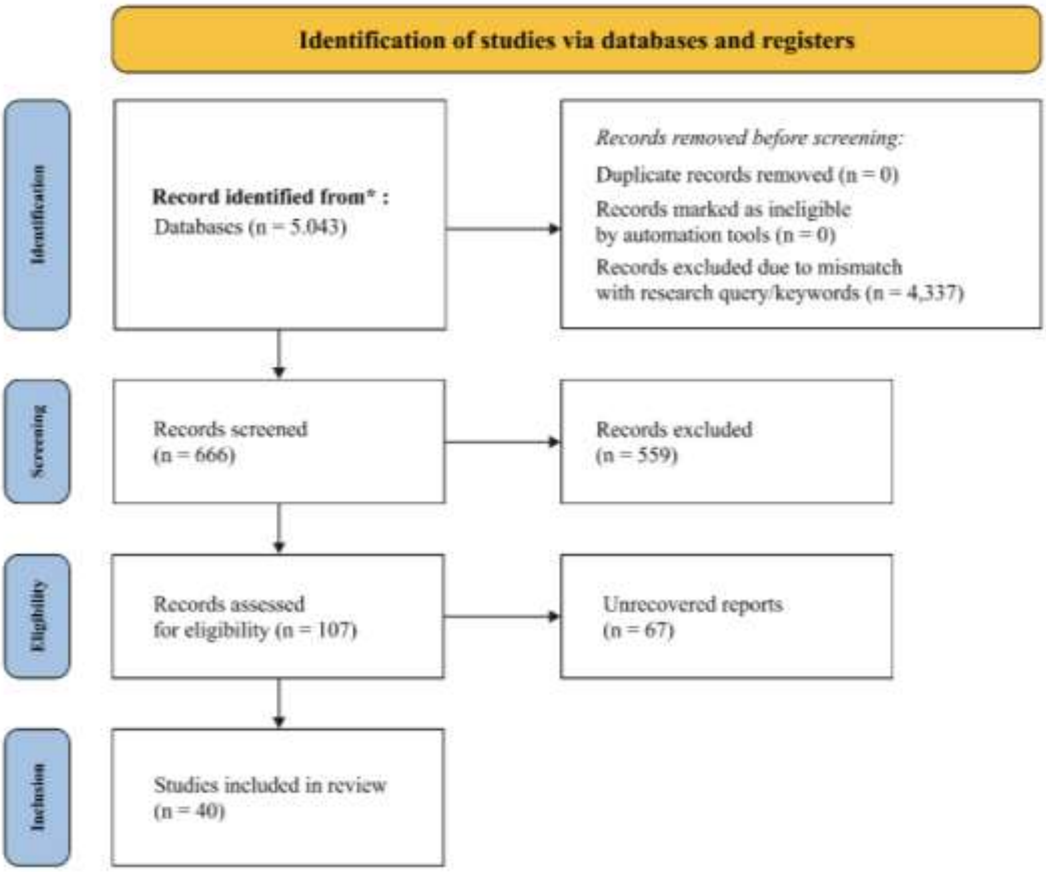

Figure 1. Prisma Flowchart

in discussions to reach a consensus on the final number of articles to be reviewed. As a result, a total of 40 journal articles were included in the final review stage.

B. Codification process

To ensure a rigorous and structured analysis, this study adopts a qualitative codification process as part of the systematic literature review. The process is designed to extract, categorize, and synthesize relevant data from the 45 selected journal articles. Codification is carried out across several dimensions, including article metadata (such as title, authors, year, and journal), research context (educational level, country, and discipline), research focus, applied theory and its construct, research methodology and its findings. A frequency analysis was also conducted to determine the occurence of factor in UTAUT construct and its extension and predecessor. Furthermore, visual representations were developed to illustrate the various influencing factors and their interrelationships, with the aim of identifying which factors exert influence over others. The coding scheme was progressively refined in response to emerging insight regarding the use behaviour of GenAI within educational context. The coded data were then syntesized into a narrative that directly address the research question. In the final stage, researchers evaluated theoretical implication of the findings grounded on UTAUT theory and in the context of behavioral intention and use of GenAI in educational purpose.

RESULT AND DISCUSSION

A. Metadata Syntesis Result

A total of 40 journal articles were collected for review and synthesis. We focused on key information and metadata from each article, including the title, year, authors, applied models, sample size, and research findings. The initial synthesis reveals that the adoption of GenAI in educational contexts is influenced by a combination of psychological, social, and technological factors. Among these, constructs from the UTAUT model and its predecessors consistently demonstrate a significant impact on GenAI usage behaviour. Additionally, the synthesis identifies several external factors beyond the UTAUT framework such as trust, perceived risk, self-efficacy, and moral and ethical considerations, which are also used to examine their influence on GenAI adoption. Some studies integrate UTAUT with other theoretical models to develop a more comprehensive understanding of user behaviour. This suggests that UTAUT constructs alone may not be sufficient to fully explain GenAI usage behaviour in educational settings. This is supported by the average variance explained, which tends to fall below 60%, indicating the need for theoretical integration and the inclusion of additional variables to better capture user behaviour.

B. Factors

To enhance understanding of the variables influencing user behaviour, variables with significant impact across studies were grouped according to their definitions. It is important to note that not all studies use consistent terminology, even when referring to conceptually identical constructs. For example, the variables Subjective Norm and Social Influence may appear under different names, yet both refer to the same underlying concept which is social pressure that encourages or discourages the use of a technology, which can be either positive or negative. Therefore, variable grouping is essential to minimize bias arising from inconsistent naming conventions. This classification focuses exclusively on exogenous variables that influence endogenous variables such as Behavioural Intention, Intention to Use, etc. Table 3 presents the results of this variable classification, highlighting the factors that influence GenAI usage behaviour in educational contexts.

Table 3. Factor Categorization and Key Findings

Factor	Conceptual Definition	Key Findings
Performance Expectancy (PE)	The degree to which individuals believe that using AI/ChatGPT will improve their performance, efficiency, or outcomes.	Several studies [11], [12], [13], [14], [15], [17], [19], [20], [21], [22], [23], [25], [26], [27], [31], [33], [34], [36], [38], [39], [44], [46], [48], [50] found performance expectancy to be a significant determinant of intention to use AI/ChatGPT. This factor consistently highlights the role of perceived usefulness and performance improvement in shaping students' behavioral intention and actual usage in academic contexts.
Perceived Usefulness (PU)	The degree to which individuals perceive AI/ChatGPT as beneficial and valuable for their tasks.	Numerous studies [11], [12], [14], [15], [17], [18], [20], [21], [23], [26], [28], [30], [32], [34], [38], [40], [46], [48] found that perceived usefulness is the strongest predictor of behavioral intention to adopt

Factor	Conceptual Definition	Key Findings
		ChatGPT. When students perceive clear benefits in academic efficiency, information quality, or skill development, they are more likely to integrate AI tools into their learning routines.
Perceived Ease of Use (PEOU)	The degree to which AI/ChatGPT is perceived as user-friendly and simple to learn.	Evidence [12], [14], [15], [18], [20], [21], [23], [26], [27], [32], [38], [40], [42], [46], [48] indicates that perceived ease of use positively influences both attitude and intention to adopt ChatGPT. This factor is particularly crucial for new users, as higher usability reduces cognitive barriers to adoption.
Social Influence (SI)	The extent to which individuals perceive that important others (e.g., peers, educators, colleagues) expect them to use AI.	Research [11], [14], [15], [18], [21], [24], [26], [32], [34], [37], [40], [41], [45], [48] found that social influence plays a central role in collectivist learning environments, where peer and instructor endorsement significantly shape adoption decisions. Nonetheless, some studies suggest that its effect varies across cultural and institutional contexts.
Effort Expectancy (EE)	The extent to which AI/ChatGPT is perceived as easy to use and free of effort.	Empirical evidence [12], [14], [20], [21], [23], [26], [27], [31], [38], [39], [44], [46], [48], [50] suggests that effort expectancy is particularly influential among students with limited prior AI experience. It has also been identified as a crucial factor in determining willingness to adopt ChatGPT in higher education.
Facilitating Conditions (FC)	The perceived availability of resources, institutional support, and technical infrastructure required to use AI effectively.	Several studies [11], [14], [15], [16], [17], [19], [20], [26], [31], [33], [34], [38], [44], [48] highlight that facilitating conditions have a direct impact on actual ChatGPT usage. Adequate organizational support, infrastructure, and training opportunities strengthen the adoption and sustained utilization of AI tools in educational contexts.

Factor	Conceptual Definition	Key Findings
Attitude (AT)	An individual's overall evaluative judgment (positive or negative) toward the use of AI/ChatGPT.	Multiple studies [18], [21], [23], [25], [28], [29], [30], [32], [34], [37], [38], [42], [46] show that positive attitudes significantly enhance intention to use AI in academic settings. Conversely, negative perceptions related to ethical concerns or performance limitations reduce willingness to adopt ChatGPT.
Trust (TR)	Confidence in the reliability, credibility, and security of AI systems.	Research [11], [12], [14], [22], [25], [27], [33], [50] underscores that trust plays a vital role in shaping adoption of ChatGPT. Users' confidence in the system's reliability, transparency, and data protection is a significant predictor of sustained engagement.
Hedonic Motivation (HM)	The extent to which the use of AI/ChatGPT is perceived as enjoyable and entertaining.	Prior findings [17], [20], [21], [26], [27], [38], [50] emphasize that hedonic motivation significantly influences behavioral intention to adopt ChatGPT. Enjoyment and perceived fun derived from interacting with AI enhance students' willingness to integrate it into their learning activities.
Self-Efficacy (SE)	An individual's belief in their capability to use AI/ChatGPT effectively.	Evidence [13], [22], [34], [36], [40], [42], [43] shows that strong self-efficacy significantly enhances adoption, as confident users adapt faster, require less support, and are more likely to sustain long-term use.
Habit (H)	The degree to which the use of AI becomes an automatic or routine behavior.	Studies [17], [19], [20], [26], [27], [38] demonstrate that habit strongly predicts continued AI use. Once ChatGPT becomes embedded in students' daily practices, it reinforces both behavioral intention and actual usage patterns in educational contexts.
Perceived Risk (PR)	Concerns regarding potential adverse outcomes of AI usage,	Findings [12], [21], [33], [34], [37], [48] indicate that perceived risk negatively influences behavioral intention toward

Factor	Conceptual Definition	Key Findings
	such as privacy violations, misinformation, or misuse.	ChatGPT adoption. Concerns over security, accountability, and the misuse of AI-generated content reduce students' willingness to integrate such tools into their learning routines.
Anxiety (ANX)	Feelings of apprehension, discomfort, or fear associated with AI usage.	Studies [16], [34], [36], [44], [47] reveal that anxiety negatively influences intention and actual use of ChatGPT, as fear of errors, misuse, or overreliance reduces adoption. Training and prior exposure help alleviate these concerns.
Ethics (E)	The principles of right and wrong that govern individuals' decisions and actions regarding AI adoption.	Research [28], [32], [42] highlights that ethical concerns shape both adoption and regulation. Users aware of ethical risks (bias, misinformation, fairness) are more cautious in using ChatGPT, while institutions emphasize integrity guidelines.
Privacy (PV)	The extent to which individuals are concerned about the protection of their personal data when using AI.	Findings [14], [31], [50] indicate that privacy concerns act as a barrier to trust and adoption. Transparent policies and institutional safeguards reduce skepticism and promote responsible use.
Price Value (PRV)	The individual's cognitive trade-off between the benefits of AI and the cost of using it.	Findings [19], [26] show that when users perceive benefits outweighing costs, adoption intention increases. Free access encourages adoption, while paywalls or subscription fees reduce intention, especially among students.

Table 3 delineates a comprehensive set of variables that influence the adoption of GenAI in educational contexts. A substantial portion of these variables originates from the UTAUT, such as performance expectancy, effort expectancy, social influence, and facilitating conditions. Several additional variables from the extended UTAUT2 framework namely hedonic motivation, habit, dan price value have also been identified as significantly influencing user behavior in certain studies. However, these three constructs appear to be less dominant compared to the core components of the original UTAUT model, particularly price value, which was found to be significant in only two studies. As is widely understood, price value refers to the trade-off between the cost incurred and the perceived benefits of using technology. In the context of GenAI, this trade-off is not directly experienced by users due to the ease of access to such technologies. In fact, several universities have facilitated GenAI access by providing institutional accounts, such as Microsoft credentials, enabling students to use GenAI Copilot without incurring any personal expense. As a result, students are generally not required to pay any fees to access GenAI services [21], [26], [51]. In many cases, institutions have facilitated access by providing official accounts, such as Microsoft credentials, which allow students to utilize GenAI tools like Copilot without incurring personal costs. Furthermore, some students perceive that even if a subscription were necessary to access GenAI, it would not be a major concern. This is due to the substantial utility these AI services offer in supporting their daily academic and personal tasks with ease [18]. Consequently, the cost-benefit consideration embedded in the price value construct is often deemed irrelevant by users, as the perceived benefits significantly outweigh any potential financial burden. Nevertheless, these foundational elements serve as the theoretical backbone for understanding user intentions and behavior. These categorizations also incorporate a range of complementary factors that extend beyond the UTAUT framework.

These additional variables including trust, self-efficacy, perceived risk, anxiety, ethics, and privacy reflect broader psychological and ethical dimensions that are increasingly relevant in AI-mediated learning environments. While UTAUT provides a robust starting point, it may not fully capture the complexity of its adoption. Variables such as trust and perceived risk can serve as analytical tools to assess users' level of confidence and caution toward GenAI platforms, and to determine whether these factors exert a significant influence on usage behaviour. Although some studies argue that trust and perceived risk do not have a notable impact due to the assured quality of corporate-backed services [11], [14], [32], these variables remain relevant for further investigation. This relevance is underscored by the emergence of numerous non-corporate GenAI platforms that often lack clear End-User License Agreements (EULAs) [12], [47]. Such ambiguity has led to a slight erosion of user trust, which in turn reduces their willingness to engage with GenAI technologies. Other variables such as ethics and privacy provide a clear depiction of the moral considerations surrounding the use of GenAI. As previously mentioned, the regulation of ethical standards, moral responsibility, and data confidentiality remains undefined and lacks clarity. This is particularly evident in student learning environments, where students are freely able to access GenAI to complete assignments with ease, often without proper guidance or a clear understanding of the underlying material [7], [21]. Moreover, students have not yet been adequately equipped with knowledge regarding ethical practices and personal data privacy when using GenAI. As a result, ethics indirectly emerges as a critical factor that warrants analysis to determine its influence on GenAI usage behavior.

This study makes a direct contribution to the advancement of the UTAUT framework by offering a behavioural perspective on the use of GenAI within educational contexts. The findings reveal that core constructs of UTAUT namely performance expectancy, effort expectancy, facilitating conditions, and social influence serve as consistent predictors of user behaviour and the extent of GenAI utilization across diverse academic populations. In addition, the study enhances conceptual understanding by systematically categorizing supplementary variables that offer a broader and more nuanced view of GenAI usage behaviour. The inclusion of these additional constructs suggests that while UTAUT provides a strong foundational model, it may not fully capture the complexity of GenAI adoption. The coexistence of both core and auxiliary constructs highlights the need for theoretical expansion and interdisciplinary integration. By acknowledging variables beyond the traditional UTAUT scope, the study supports the development of more comprehensive models that better reflect the diverse motivations, perceptions, and concerns of educational stakeholders.

CONCLUTIONS

This study provides a comprehensive synthesis of behavioral factors influencing the adoption of Generative AI (GenAI) in educational contexts through a systematic literature review of 40 peer-reviewed articles. While core constructs from the Unified Theory of Acceptance and Use of Technology (UTAUT) remain foundational, the findings emphasize that these alone cannot fully explain user behavior. The inclusion of complementary variables such as trust, perceived risk, self-efficacy, hedonic motivation, and ethical concerns reveals the layered complexity of GenAI usage, shaped by both technological affordances and individual perceptions. The integration of UTAUT with other theoretical models, including TAM, TPB, and SCT, enhances the explanatory depth and reflects the need for multidimensional frameworks that accommodate psychological, moral, and contextual influences. This study also contributes to the theoretical development of UTAUT by categorizing auxiliary constructs and proposing a conceptual model that captures the interplay between intention, behavior, and external conditions. These insights offer valuable implications for researchers, educators, and policymakers seeking to foster responsible, equitable, and pedagogically sound integration of GenAI in academic environments. Future research should continue to validate and expand these frameworks across diverse educational settings, ensuring that GenAI adoption aligns with ethical standards and supports meaningful learning outcomes.

Acknowlegdement

We would like to express our sincere gratitude to Telkom University, specifically the Information Systems Department, for providing the laboratory facilities necessary for us to complete this review. We will continue to support Telkom University in developing research on GenAI Adoption in Education.

Author Contributions

A.A.H, T.A.R, Review and editing, Methodology, N.A.R, R.V.F, Formal analysis. T.A.R, I.M.P, R.V.F, Writing -original draft, Investigation, A.A.H, Funding acquisition, I.M.P, Data curation.

Funding

Not applicable.

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