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Article

Role of Educational Technology in Students` Academic Achievement: Testing the Mediation of E-Efficacy

Meryem Fati
Arab Open University, Bahrain.
Email: f.fati.meryem@gmail.com

Nadeem Khalid
Anglia Ruskin University, Cambridge, United Kingdom.
Email: nadeem.khalid@aru.ac.uk

Abstract

This study explores the impact of Educational Technology (ET) on students' Academic Achievement, with a particular focus on the role of E-Efficacy. A total of 199 valid responses were collected from students through a survey instrument to test the proposed relationships. The analysis reveals a positive correlation between students' AA and the educational technologies they utilize, with EE identified as a significant mediator in this relationship. The findings indicate that students' EE enhances as they engage with educational tools effectively, leading to improved academic performance. This research contributes to the existing literature on ET, underscoring the necessity of fostering EE among students to fully leverage the advantages of these technologies. The results are consistent with previous studies that highlight a positive relationship between Self-Efficacy (SF) and learning outcomes, suggesting that interventions aimed at building confidence in the use of educational technologies could have a transformative effect on students' academic results.

Keywords

ET, EE, AA, SE.

Correspondence to

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Introduction

The Growing Role of ET in Education

ET plays a pivotal role in the ongoing transformation of the educational landscape, reshaping both content and processes. The integration of information and communication technology (ICT) in academic contexts has gained widespread adoption, driven by the reindustrialise of society and evolving educational philosophies. The roots of contemporary ET can be traced back to the instructional use of audio and video media in the mid-20th century; however, its significant expansion began with the introduction of personal computers in the 1980s, followed by the rise of the Internet a decade later. This era marked a critical turning point, as the proliferation of these technologies opened up new possibilities for communication and educational engagement. According to Cuban (2001), the transition from a lack of computers to their widespread adoption heralded a fundamental shift in educational systems, positioning technology at the forefront of educational practice, although the rate of acceptance varied significantly and was often accompanied by skepticism. In the realm of online learning, technology is essential for enhancing educational accessibility, particularly for learners in remote or underserved areas. The advent of online learning tools and resources has democratized access to quality education, enabling broader participation. The reliance on technology during the shift to virtual education, especially amid the COVID-19 pandemic, underscores both the advantages and challenges associated with ET. A report by the World Bank (2020) highlights the critical role of digitalization in education during the pandemic, affirming that technology has become indispensable in delivering educational services effectively at scale.

One of the most significant benefits of ET is its emphasis on learner-centered education, distinguishing it from traditional instructional approaches. Current research indicates that students can leverage adaptive learning technologies to enhance their learning efficiency by mitigating boredom and frustration. These technologies adjust content based on students' interactions and performance, thereby creating a more personalized learning experience. Pane et al. (2014) assert that cognitive tutors exemplify effective adaptive systems, allowing students to engage with relevant and beneficial knowledge tailored to their individual needs. Furthermore, ET enhances the collaborative and interactive dimensions of learning. Tools such as Learning Management Systems (LMS), video conferencing platforms, and collaboration software enable real-time interaction between students and educators, irrespective of physical location. These technologies promote a community of inquiry that fosters critical thinking and cooperative learning, as discussed by Garrison (2003). Additionally, learning analytics analyzing data on student learning behaviors serve as a valuable tool for identifying students at risk of underperforming. As Siemens and Baker (2012) note, those engaged in technology-supported education often utilize analytics to predict, comprehend, and significantly enhance educational outcomes. This data-driven approach provides insights that can inform instructional strategies and interventions, ultimately improving the educational experience for students.

The impact of ET on students' academic performance has garnered increasing scholarly attention in recent years. Despite extensive research in this domain, significant gaps remain in understanding the specific mechanisms through which ET influences AA. One such overlooked aspect is EE, defined as individuals' belief in their capacity to effectively utilize technology for specific purposes. Numerous studies have focused primarily on the direct effects of computers and other educational technologies on students' academic performance, emphasizing how information and communication technology (ICT) devices can enhance learner engagement, facilitate individualized learning experiences, and reach previously underserved populations (Alavi & Leidner, 2001; Pane et al., 2014). While these studies provide valuable insights, they frequently fall short by neglecting the psychological and behavioural variables that may mediate the relationship between technology use and AA. EE, an extension of Bandura's SE efficacy concept, refers to an individual's belief in their ability to perform specific learning activities using appropriate technologies to achieve desired outcomes (Bandura, 1997). Although a plethora of research has explored SE across various educational contexts, limited attention has been paid to its adaptation to the digital learning environment, commonly referred to as EE, and its potential mediational role in the relationship between ET and AA. Many researchers who address EE tend to treat it as a secondary variable rather than recognizing its critical significance (Compeau & Higgins, 1995; Moos & Azevedo, 2009).

This oversight regarding the importance of EE represents a notable shortcoming in the literature, suggesting a lack of recognition for the myriad factors that contribute to students' AA when engaging with technology. Addressing this gap is essential, particularly given the increasing integration of technology in educational settings, where effective utilization of these tools can profoundly impact learners' academic outcomes. The proposed research aims to empirically investigate the mediating role of EE in the relationship between ET and students' AA. By doing so, this study seeks to enhance our understanding of how digital tools affect practical education, ultimately facilitating the development of improved educational technologies and pedagogical strategies. The primary objectives of this research are to define and examine the relationship between students' AA and their utilization of ET. Additionally, the study aims to analyse the function of EE as a mediator in the correlation between the adoption of ET and AA. Furthermore, it seeks to investigate both the positive and negative impacts of EE on students' academic outcomes.

Lastly, the research will identify and elucidate, supported by empirical evidence, the potential mediating factors in the association between ET, EE, and AA. This study holds significant implications for advancing educational practices and policies by providing valuable insights into the integration of technology in education and its effects on AA. Understanding how ET can enhance academic performance is critical for educators, as this knowledge can inform the adoption of innovative teaching methods that leverage technology to promote better learning outcomes. By focusing on EE, the study emphasizes the importance of students' beliefs in their technological capabilities, which can lead to increased self-confidence and participation in learning activities. High EE is associated with improved academic performance, highlighting the necessity of implementing educational interventions that bolster students' confidence in their technological skills, ultimately fostering greater engagement. Moreover, the findings from this research may serve as a basis for policymakers to advocate for increased funding for ET initiatives. Such investments, coupled with efforts to enhance students' proficiency in using these tools, could lead to the development of policies aimed at improving access to technology and ensuring effective utilization in educational settings.

The study also addresses issues of inequality in education by illustrating how factors like ET and EE impact academic performance. This research has the potential to inform policymakers about the disparities in technology access and usage, guiding the formulation of effective measures to bridge the digital divide, thereby enabling students from diverse economic backgrounds to benefit from technology in their educational pursuits. In terms of theoretical contributions, this study enriches the existing body of knowledge by examining the mediating role of EE in the relationship between the use of ET and AA. This exploration facilitates a deeper understanding of the factors that can be optimized to implement successful technology integration in education and lays the groundwork for future research in this area. Lastly, the findings of this study are expected to influence the development of future educational curricula and programs by highlighting the practical use of technology in teaching and learning. Emphasizing EE equips educators with strategies that extend beyond mere technological engagement, encouraging students to utilize these tools effectively for enhanced learning outcomes.

Research Questions

RQ1: How does ET impact student AA?
RQ2: Does ET influence EE?
RQ3: Does EE mediate the association between ET and AA?

Literature Review

ET: Theoretical Perspectives and Empirical Evidence

The integration of ET is fundamentally transforming traditional educational paradigms, impacting both teaching and learning processes. This literature review synthesizes key concepts and pertinent studies that explore the integration of educational technologies in learning environments and their resultant effects on academic outcomes.

Theoretical Frameworks: SCT

The role of information and communication technology (ICT) in educational settings can be effectively understood through the lens of SCT. This theory posits that knowledge acquisition occurs within a social context, influenced by observation of others, personal beliefs (SE), and environmental factors. Bandura (1986) and Dung et al. (2022) asserts that SE the belief in one's capability to perform specific tasks plays a crucial role in students' interactions with instructional technologies. Students exhibiting higher levels of SE are more likely to engage actively with educational technologies, which in turn enhances their academic performance.

Constructivist Theory

Constructivism, particularly as articulated in the work of Vygotsky (1978), emphasizes that learning is not a passive reception of information but an active construction of knowledge. ET serves as a vital tool for fostering creative problem-solving and critical thinking, allowing students to engage with content more dynamically. Vygotsky (1978) and Cembellín, Barrio and Mairal (2022) highlights the importance of social interaction in the learning process, which can be effectively facilitated through educational technologies that promote collaborative learning.

Evidence-Based View

Impact on Students' AA

Extensive literature indicates that ET positively influences student achievement. A meta-analysis by Schmid et al. (2014) unequivocally established that technology-enhanced instructional methods, particularly those fostering interactive and multimedia engagement, significantly improve learner outcomes. Similarly, Tamim et al. (2011) demonstrated that e-learning environments, enriched with technology, yield better student performance compared to traditional instructional methods.

Impact of EE: The Degree of Technology Integration

EE, a specific form of SE related to technology use, is critical in determining how effectively students utilize educational technologies. A robust sense of EE is essential for the successful implementation of ET, directly correlating with improved academic performance. Liaw, Huang and Chen (2007) and Radif (2023) further corroborated this by finding that students' EE regarding online learning tools positively relates to their satisfaction and success in digital courses. Despite the advantages of ET, several barriers to its effective application persist. Selwyn (2016) identified key obstacles, including limited access, insufficient teacher training, and resistance to change, which hinder the realization of ET's full potential, particularly in under-resourced educational settings.

EE: Definition and Role in Student Learning and Technology Use

EE pertains to individuals' confidence in their ability to effectively utilize ICT within educational contexts. According to Bandura's (1986) framework of SE, this concept significantly influences students' perceptions, actions, and emotional responses concerning their capacity to employ technology for teach (Fati et al., 2019; Mohammed, Al-Qahtani, & Takken, 2023). In this regard, EE governs students' levels of interaction, engagement, and the educational benefits they derive from digital tools (Compeau & Higgins, 1995). EE is a decisive factor in shaping how students engage with technology in their studies and the resultant impact on their academic performance. High levels of EE empower students to utilize educational technologies effectively, leading to enhanced learning outcomes. Students confident in their technological capabilities are more likely to engage actively in learning activities, fostering deeper understanding. Moreover, enhanced EE promotes self-regulation, particularly in online and blended learning contexts where learners must often navigate their educational processes independently (Rakover, 2023; Zimmerman, 2000). Students exhibiting strong EE are inclined to set learning goals, monitor their progress, and adjust their strategies, all of which positively influence AA. EE not only affects learning outcomes but also influences the degree to which students employ technology in practical situations. Students with high EE are more likely to embrace new technologies for educational purposes, actively seeking out tools to enhance their learning (Compeau & Higgins, 1995). Conversely, those with lower EE may avoid utilizing technology or engage superficially, thereby missing out on its educational benefits. Interventions aimed at improving EE have demonstrated positive outcomes, fostering more favourable attitudes toward technology and promoting increased usage. For instance, training programs that enhance students' technological confidence often lead to greater willingness to engage with new tools, ultimately boosting academic performance (Muthuswamy & Sudhakar, 2023; Wang, Shannon, & Ross, 2013).

EE as a Mediating Variable

SE, a central component of Bandura's SCT, significantly influences students' academic performance and engagement (Bandura, 1997; Senathirajah et al., 2023). It has been recognized as a vital mediating variable in numerous studies exploring the relationship between educational practices and learning outcomes. Zimmerman (2000) noted that SE mediates the relationship between self-regulation strategies and achievement goals, indicating that students with higher SE are more likely to adopt effective learning strategies, leading to improved academic outcomes. Schunk and Pajares (2002) emphasized that SE shapes students' interpretations of their prior educational experiences, which subsequently affects their academic performance in future endeavours. Students with positive past experiences are likely to possess higher SE, motivating them to excel in their current academic pursuits. This underscores the necessity of fostering SE to maximize educational benefits.

EE as a Mediator in Technology-Enhanced Learning

Several studies have examined EE as a mediating factor in the adoption of ET and its impact on student performance. According to prior studies EE mediates the relationship between students’ interactions with technology and their AAs, indicating that higher EE correlates with more profound engagement and improved learning outcomes. In a complementary study, Liaw and Huang (2013) explored the factors affecting students' acceptance of e-learning systems, highlighting EE as a mediator between perceived ease of use and overall satisfaction with technology. This finding underscores the necessity of fostering students' belief in their technological abilities to ensure successful educational outcomes. Wang et al. (2013) also illustrated that EE serves as a mediating variable between online instructional design and student performance, revealing that well-structured courses enhance students' EE, subsequently influencing their success. These findings affirm that EE is crucial for leveraging technology to achieve meaningful educational improvements.

Theoretical Framework: SCT and the Concept of SE

Developed in the 1980s by Albert Bandura, SCT has become a cornerstone in the study of behaviour, educational practices, and motivation. SCT posits that learning occurs in a social context, influenced by the interplay of three factors: personal (cognitive processes and emotions), environmental (social influences and feedback), and behavioural (Bandura, 1986; Mabkhot & Al-Ameryeen, 2023). This triadic model implies that individuals not only shape their environments but are also shaped by them. SE, a central tenet of SCT, encapsulates individuals' beliefs about their capacity to effect change in their environments. This construct significantly impacts how individuals think, feel, and behave, making it a critical variable in educational contexts.

Defining SE within SCT

SE influences various aspects of students’ educational experiences, including task selection, effort, persistence, and the ability to overcome challenges. Research by Bandura (1997) demonstrated that individuals with high SE are more likely to initiate tasks, persist through difficulties, and ultimately achieve success. In contrast, low SE may lead to avoidance of challenging tasks and diminished effort, resulting in suboptimal performance. Evidence suggests that SE operates within students’ educational experiences, significantly impacting their academic outcomes. For instance, students who are confident in their ability to master specific content are more likely to employ effective learning strategies, seek assistance when needed, and persist in their efforts. This positive feedback loop reinforces cognitive SE and enhances academic performance (Zimmerman, 2000).

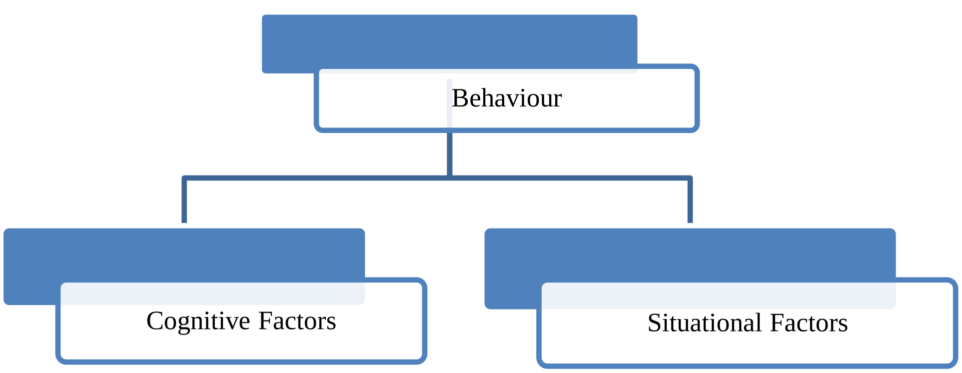

Figure 1: *Social Cognitive Theory (Albert Bandura).*

EE: Technology SE in Educational Contexts

EE represents a specialized form of SE, focusing on individuals' confidence in their ability to effectively utilize technology in learning environments. As technology becomes increasingly integrated into education, recognizing the importance of EE is essential for creating effective learning experiences. EE pertains to students' beliefs in their skills to successfully navigate technology-enhanced learning environments (Compeau & Higgins, 1995). The notion of EE aligns with SCT, illustrating how beliefs about technological abilities influence behaviour in educational settings. Students with high EE are more inclined to experiment with educational technologies, thereby enhancing their learning experiences. Conversely, those with low EE may shy away from utilizing these tools, limiting their learning opportunities (Liaw et al., 2007).

Application of SCT in Instructional Technology

The concepts of SE and EE can be effectively analysed through the lens of SCT in the context of instructional technology. This perspective emphasizes the interplay of personal beliefs (e.g., EE), environmental supports (e.g., availability of technology), and behavioural outcomes (e.g., technology use) in shaping students' learning experiences. Prior literature illustrate that EE mediates the relationship between student engagement with online learning platforms and academic performance. This finding underscores the importance of fostering EE to optimize technology's role in enhancing educational outcomes. SCT provides a valuable framework for understanding how ET can improve student learning. Transitioning from SE to EE is particularly relevant in today's technology-driven educational landscape. By enhancing EE, educators can facilitate greater engagement with digital technologies, ultimately leading to improved academic performance. Thus, SCT and its constructs offer a robust theoretical foundation for examining the effects of educational technologies on student achievement.

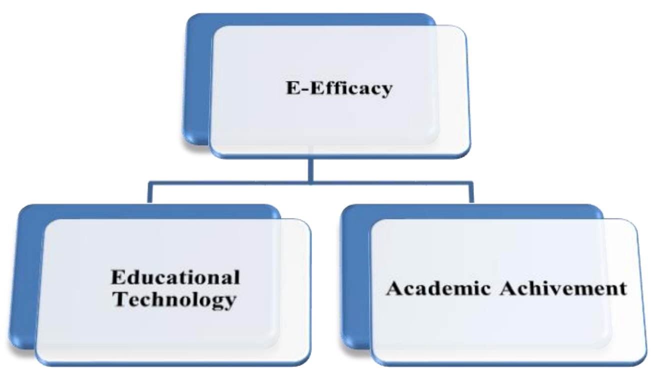

Figure 2: *Research Framework.*

Research Design Sample and Population

The primary objective of the research design is to establish a comprehensive framework for conducting the study, detailing the types of research, methodologies, target population, data analysis strategies, and procedural tasks. This design delineates the boundaries of the study and sets clear parameters for evaluating outcomes. In this research, a cross-sectional survey design was employed to assess the impact of ET in relation to EE within both distance and campus-based learning environments. The target population comprises secondary and tertiary students studying in the UK who engage in both offline and online learning methods. A structured questionnaire was administered to 270 students, consisting of 12 items that were adopted and adapted to reflect the constructs of the study: ET, EE, and AA. Data collection was facilitated using Google Forms, which provides extensive coverage and enables rapid response collection. The survey yielded a total of 247 completed responses, resulting in a response rate of 91.48%. However, 48 questionnaires were excluded from analysis due to incompleteness. Consequently, 199 fully completed questionnaires were available for analysis, yielding a final completed response rate of 80.56%. The response rate achieved is consistent with established research benchmarks. Livingston and Wislar (2012) indicates that any response rate exceeding 30% is considered satisfactory in survey research, while Kimball and Loya (2017) assert that a target of 35% is appropriate for organizational surveys. Furthermore, a prior study supports the notion that for non-probability sampling, a sample size ranging from 30 to 500 is deemed acceptable. Therefore, the response rate of 80.56%, translating to 199 usable responses, provided a robust basis for data analysis. This section concludes with a summary of the data collected, presented in Table 1, which details the responses given by the participants. The analysis of these responses will contribute to understanding the influence of ET and EE on AA within the studied population.

Table 1: *Response Rate.*

	No of Responses	%
Distributed Questionnaires	270	100%
Questionnaires Received	247	91.48%
Not Included Questionnaires	48	-
Number of Valid Responses	199	80.56%

Normality Assessment

The assessment of normality is a critical component of multivariate analysis, essential for validating both potential and actual scores of dependent variables (Burdenski Jr, 2000). While many statistical methods commonly assume normality, Partial Least Squares Structural Equation Modelling (PLS-SEM) offers a degree of flexibility that allows for model evaluation without stringent normality requirements, applicable to both general populations and their respective subsamples. Various statistical techniques are utilized to evaluate normality, including skewness and kurtosis statistics, stem-and-leaf plots, normal probability (P-P) plots, and formal tests such as the Kolmogorov-Smirnov test, which is particularly prominent in social science research (Mooi & Sarstedt, 2011). It is important to note that certain analyses, especially those grounded in correlation, may be adversely impacted by skewed data (Chernick, 2011). This emphasizes the necessity of confirming the normal distribution of data prior to conducting specific analyses (Hair et al., 2014). To visually assess normality, researchers often utilize histograms, P-P scatter plots, and normal distribution plots. These methods provide a graphical representation to confirm that the data do not significantly deviate from expected patterns. In this investigation, all variables were anticipated to conform to a normal distribution, as illustrated in Figures 3 and 4. This visual confirmation supports the validity of the subsequent analyses and findings derived from the data.

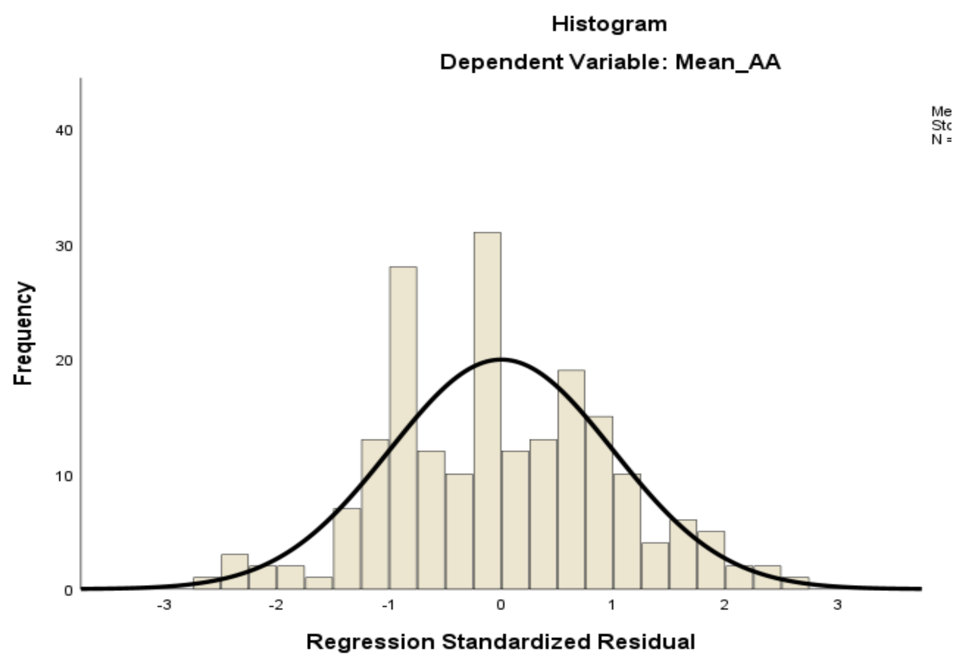

Figure 3: *Histogram Mean_AA.*

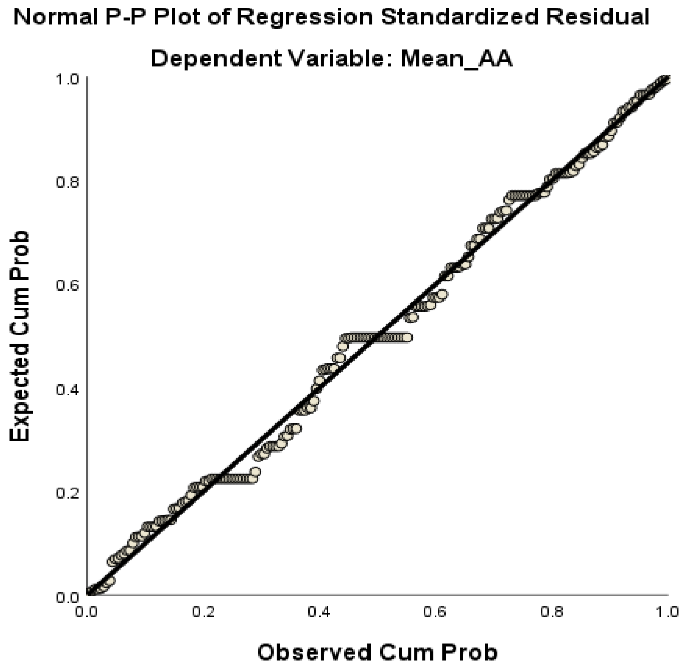

Figure 4: *Normal P-P Plot of Mean_AA.*

The researcher conducted a second normality test to assess data distribution in terms of skewness and kurtosis (Tabachnick & Fidell, 2007). Kurtosis indicates the shape of the distribution: positive kurtosis reflects a peaked distribution, suggesting that data points are sharply clustered around the mean with long tails, while negative kurtosis signifies a flatter distribution. In terms of skewness, positive skewness indicates a tail extending to the right, whereas negative skewness suggests a tail extending to the left. For a distribution to be considered normal, both skewness and kurtosis should be close to zero. According to established guidelines, skewness values greater than 1 indicate a significant skew, while values above +1 suggest excessive peakiness. Conversely, skewness values below -1 indicate a flatter distribution. Hair et al. (2010) propose acceptable ranges of ±2 for skewness and ±7 for kurtosis. As presented in Table 2 of the descriptive statistics, the observed values of skewness and kurtosis are around one, which falls within the acceptable range of ±2, thereby indicating that the data distribution aligns with the assumption of normality (Hair et al., 2010). This finding reinforces the suitability of the data for further statistical analysis.

Table 2: *Descriptive Statistics.*

	N	**Minimum**	**Maximum**	**Mean**	**Std. Deviation**	**Skewness**		**Kurtosis**	
	Statistic	**Statistic**	**Statistic**	**Statistic**	**Statistic**	**Statistic**	**Std. Error**	**Statistic**	**Std. Error**
ET1	199	1	5	3.87	.864	-.371	.172	-.307	.343
ET2	199	2	5	3.81	.853	-.126	.172	-.791	.343
ET3	199	1	5	3.88	.818	-.288	.172	-.225	.343
EE1	199	2	5	3.94	.857	-.273	.172	-.815	.343
EE2	199	2	5	3.94	.836	-.210	.172	-.881	.343
EE3	199	2	5	3.99	.816	-.319	.172	-.673	.343
AA1	199	2	5	3.89	.815	-.133	.172	-.805	.343
AA2	199	2	5	3.95	.851	-.251	.172	-.868	.343
AA3	199	2	5	4.03	.775	-.175	.172	-.964	.343
Valid N (List Wise)	**199**								

Demographic Overview

The demographic composition of the sample reveals a balanced female-to-male ratio, contributing to diversity within the age groups of the participants. Among the 199 respondents, 98 (49.2%) identify as women, while 101 (50.8%) identify as men, indicating an almost equal representation of genders in the study population. In terms of age distribution, a significant majority, comprising 62.8% (125 respondents), fall within the 15-20 year age range. Participants aged 20-25 years account for 27.6% (55 respondents), and those aged 25 years and above represent 9.6% (19 respondents). This distribution highlights a predominance of younger participants in the study, which aligns with the focus on educational technology and its impact on academic achievement. The emphasis on a younger demographic is particularly relevant, as this group is likely to engage more with technology-enhanced learning environments.

Table 3: *Demographic Table (Gender).*

SEX	Number	%	Cumulative %
F	98	49.2	49.2
M	101	50.8	100
Total	199	100	100

Table 4: *Demographic Table (Age).*

	Years	Frequency	%	Cumulative %
	15 - 20 Years	125	62.80%	62.80%
Valid	**20 - 25 Years**	55	27.60%	90.40%
	25 Years and Above	19	9.60%	100.00%
Total		199	100.00%	100.00%

Assessment of Measurement Model

The outer measurement model is a crucial aspect of structural equation modelling (SEM), as it delineates the relationships between specific measured variables (indicators) and their corresponding underlying variables (latent variables). This model necessitates the validation of the structural framework, specifically assessing whether the indicators accurately represent the intended constructs. Within this context, several metrics are employed to evaluate reliability and validity. Cronbach's alpha and composite reliability are commonly used to assess the internal consistency of the indicators. Additionally, average variance extracted (AVE) serves as a key metric for measuring construct validity (Hair et al., 2017; Henseler, Hubona, & Ray, 2016). These measures collectively ensure that the model accurately reflects the theoretical constructs it aims to represent.

Table 5: *Construct Reliability and Validity.*

Constructs	Alpha	CR (rho_a)	CR (rho_c)	AVE
AA	.844	.848	.906	.762
EE	.902	.903	.939	.836
ET	.795	.8	.88	.71

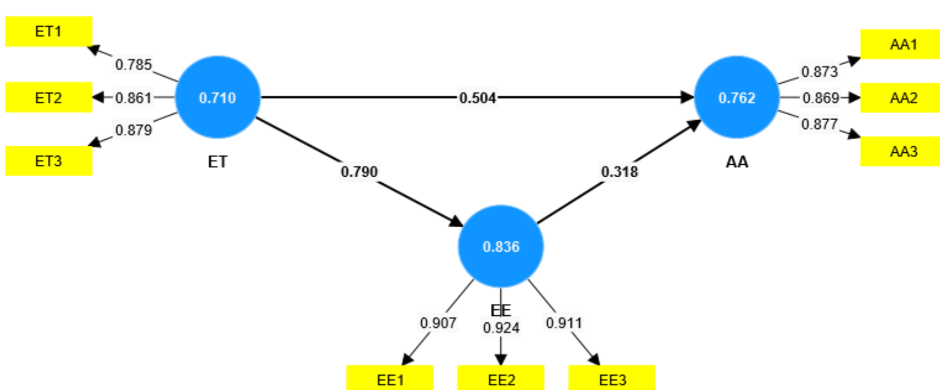

Figure 5: *Measurement Model.*

The constructs of ET, EE and AA exhibit comparable levels of reliability and validity as indicated by the measures utilized in this study. Table 5 displays the Cronbach's alpha coefficients for the four constructs, showing values of ET: 0.795, EE: 0.902, and AA: 0.844. All these coefficients exceed the recommended threshold of 0.70, confirming the internal consistency and reliability of the constructs (Nunnally & Bernstein, 1994). Moreover, the composite reliability (rho_c) factors further substantiate the robustness of these constructs, with values recorded as ET: 0.88, EE: 0.939, and AA: 0.906. These figures exceed the necessary benchmarks for validating the measurement model's consistency (Hair et al., 2010). Additionally, the average variance extracted (AVE) values for the constructs ET: 0.71, EE: 0.836, and AA: 0.762 are all greater than the 0.50 threshold. This indicates that each construct accounts for more than 50 percent of the variance in their respective items, thereby supporting the validity of the constructs as outlined by Fornell and Larcker (1981).

Assessment of Structural Model

The correlation between EE and AA reveals a positive and significant effect, as indicated by a path coefficient of 0.318 (p = 0.003). Table 6, 7 and Figure 6 illustrate the relationships among ET, EE and AA. This finding suggests that an increase in EE is associated with improved academic performance. Furthermore, the direct effect of ET on AA is both significant and positive, evidenced by a path coefficient of 0.254 (p = 0.019), indicating that the effective application of ET directly enhances student performance. The correlation between ET and EE is also substantial, with a path coefficient of 0.79 (p = 0.000). This strong association implies that ET effectively enhances students' EE. Collectively, these findings highlight the contributions of both ET and EE to AA, positioning EE as a crucial mediator in this relationship. These results align with prior research, including Zheng et al. (2016), which demonstrated that technological interventions significantly enhance student SE, leading to improved academic outcomes. Similarly, Scherer and Siddiq (2019) confirmed that EE mediates the relationship between ET and AA. Such studies collectively underscore the essential role of EE in transforming the use of ET into tangible academic performance. This research adds to the existing evidence regarding the positive impact of ET interventions on AA through the lens of EE, reinforcing the need to prioritize these factors in practical educational settings to enhance student performance. Additionally, Table 6 highlights the significant mediating effect of EE) in the relationship between ET and AA. The indirect path from ET to AA through EE shows a path coefficient of 0.251, accompanied by a t-statistic of 2.909 and a p-value of 0.004, confirming statistical significance. This suggests that EE partially mediates the relationship, indicating that the utilization of ET positively influences EE, which in turn enhances AA.

Table 6: *Path Coefficients and Significance Testing.*

Relationship	Beta Value	Mean (M)	SD	T Stats	P Values
EE -> AA	.318	.32	.106	3.008	0.003
ET -> AA	.254	.256	.108	2.347	0.019
ET -> EE	.79	.79	.034	23.401	0

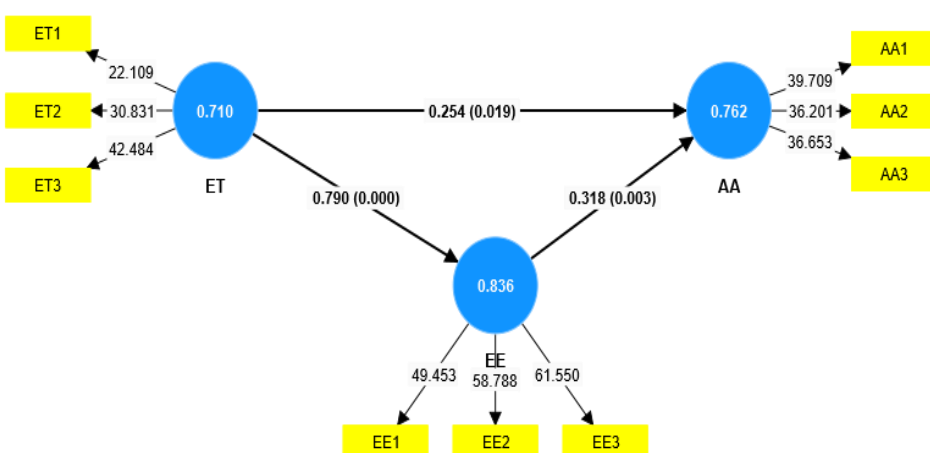

Figure 6: *Structural (Inner) Model.*

Table 7: *Mediating Effect.*

Constructs	Beta Value	Mean	SD	T Stats	P Values
ET -> EE -> AA	0.251	0.253	0.086	2.909	0.004

Conclusion

This study provides empirical evidence demonstrating that the use of ET significantly enhances AA, with EE serving as a crucial mediator in this relationship. Building on Bandura's (1997) research on SS and academic performance, the findings highlight that SS influences cognitive functions such as goal-setting. Schunk and Pajares (2002) further emphasized that students with higher levels of SS outperform their peers in learning experiences involving technological tools. This research extends this body of work by confirming that EE defined as a specific form of SS related to the effective use of information and communication technologies correlates positively with AA. In summary, this paper underscores the importance of EE in the practical implementation of ET. The findings clearly demonstrate that EE mediates the relationship between ET and AA. Through robust quantitative analysis, the study successfully addressed the research questions posed.

Limitations and Future Recommendations

One limitation of this study is the reliance on surveys for data collection, which may introduce biases such as social desirability or self-verification bias. Participants might exaggerate their levels of EE or downplay their usage of ET, potentially impacting the validity of the results. Additionally, the focus on a single target population limits the generalizability of the findings to diverse educational contexts or age groups. The cross-sectional design further constrains the ability to draw causal inferences regarding the relationships among ET, EE, and academic performance. Moreover, while this study primarily centres on EE as a mediator, it does not account for other potential mediators or moderators, such as motivation, prior technology experience, or teacher support. Future research should consider incorporating these variables to enrich the understanding of how ET impacts AA. To address the limitations identified in this study, future research should expand the respondent pool to include students from varied nationalities, educational levels, and age groups. Longitudinal studies are recommended to assess EE and ET over time, thereby providing a clearer understanding of their relationship with AA. Additionally, qualitative methods such as focus group discussions or interviews could yield deeper insights into students' perspectives on ET. Finally, it is advisable for future studies to explore other mediating or moderating variables that may influence the relationship between ET and academic performance, including factors such as student motivation, teacher validation and feedback, and prior technological exposure.

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