The Impact of Educational Technology on Cognitive and Emotional Learning Outcomes

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ABSTRACT:

Educational technology has become a key component of higher education, yet its effects on cognitive and emotional learning outcomes remain unclear. This study examined the impact of educational technology on academic performance, course completion, learning satisfaction, and learning motivation using two secondary datasets comprising 326 and 1,317 observations, respectively. Descriptive statistics, correlation analysis, reliability testing, logistic regression, and ordinary least squares regression were employed. The findings revealed limited effects of educational technology engagement variables on cognitive outcomes. Although the course completion model was significant overall, none of the individual technology engagement indicators significantly predicted performance, and the CGPA model was non-significant. In contrast, strong effects were observed for emotional outcomes. Technostress and online learning misfit significantly predicted learning satisfaction and motivation, explaining 58.3% and 54.9% of the variance, respectively. Significant positive relationships were also identified among the emotional learning constructs. The results suggest that educational technology exerts a stronger influence on students' emotional learning experiences than on measurable academic performance. Evaluations of technology-enhanced learning should therefore consider both cognitive and emotional dimensions to better understand educational effectiveness.

Keywords: educational technology, cognitive learning outcomes, emotional learning outcomes, technostress, online learning misfit.

1. Introduction

Educational technology has now become an important part of higher education today as it has affected how learning takes place through delivery, accessibility, and assessment. As there has been an immense growth of digital learning tools, various technological devices such as LMS, interactive platforms, learning software, and many others have been incorporated into the process of instruction and learning. This process has provided flexibility, accessibility, and opportunities for independent learning. The use of educational technologies has grown in educational settings according to Granić (2022), who stressed the significance of educational technologies in the present learning context. The use of educational technologies has even altered the methods of instruction and promoted learning through an interactive experience. Communication, collaboration, instant feedback, and customization have made the learning process very engaging, which was facilitated by digital technologies. According to Tuma (2021), educational technology contributes to classroom interaction and active participation of students. Likewise, Dzobelova et al. (2020) suggested that technological educational tools have turned into valuable assets for higher education institutions that wish to increase the effectiveness of their teaching practices and ensure their accessibility. The development of technology-enhanced learning is driven by the widespread introduction of learning management systems that allow teachers to create an organized course content, evaluate learners' progress, and engage in interaction. Learning management systems have grown particularly crucial in higher education, which sees the continuous proliferation of blended and online learning approaches. As was found by Fearnley & Amora (2020), perceived usefulness and ease of use play a decisive role in successfully adopting learning management systems by university learners, underscoring the role of technology acceptance in educational settings. Increased use of educational technology has raised significant curiosity regarding its impact on student learning outcomes. Learning outcomes are usually regarded as being multidimensional, meaning they include both cognitive learning outcomes such as academic achievements and performances and affective learning outcomes including satisfaction, motivation, and engagement. The need for an understanding of educational technology's impact on learning outcomes lies in the fact that effective learning encompasses not just knowledge acquisition but also positive psychological and motivational experiences. Various studies have shown conflicting results when it comes to educational technology's impact on cognitive learning outcomes. Some research indicates that technology-supported learning environments are beneficial for improving academic performance owing to increased accessibility of learning resources, interactive instruction, and personalized feedback provided. Yeung et al. (2021) found out that educational technology could enhance objective learning outcomes provided that certain instructional conditions are met. Similarly, Sen and Leong (2020) identified educational technology as an essential element of technology-enhanced learning models aimed at knowledge acquisition and skill development. Nevertheless, there are cases where changes in the level of cognitive performance are not observed. It might be due to the difference in infrastructure, teaching methodology, features of learners, and their engagement in the process of education through technological tools. Sargent & Calderón (2021) stated that the use of educational technologies was not the determinant of success in education because its value lay mainly in the way it was incorporated in teaching practices. Such findings show that educational technologies do not necessarily guarantee improvement in students' cognitive skills. On the contrary, emotional results of learning can often be traced while using such tools. Technologies can help motivate, satisfy, and increase the confidence of learners in their knowledge and skills by increasing the level of independence and flexibility in studying. Yu & Deng (2022) proved that educational technologies were strongly linked to learner satisfaction, motivation, self-efficacy, and performance through meta-analysis. This suggests that emotional dimensions of learning may be particularly responsive to students' experiences with digital technologies. But introduction of technology has brought a lot of problems to the learners. For instance, a frequent occurrence in the adoption of technology is technostress; a term defined as the stress created by the use of technology and technology related requirements. Learners can experience technostress while adapting to digital platforms, managing technology complexity, and engaging in ongoing interactions online. Kumar (2024) found that technostress may be very detrimental to the mental health, attitude and performance of students in technology rich environments. Fit has also emerged in relation to technology use. One aspect of the regulatory fit theory is fit, which is the match between the individual's nature and learning environment, which affects motivation and learning effectiveness. It can be assumed that the lack of fit of learner environment can undermine the quality of education provided using technology (Janson et al., 2023). Nevertheless, the understanding of educational technology and student learning is still far from complete. Most contemporary research tends to consider academic or emotional outcomes in isolation, resulting in a piecemeal understanding of the efficacy of educational technology. Furthermore, despite the mixed findings related to the effects of educational technology on cognitive outcomes, and less attention has been paid to the concurrent examination of cognitive and emotional learning dimensions. The increasing importance of technology-enhanced learning calls for more attention to technology-related experiences such as technostress and learner–environment fit in the evaluation of educational outcomes. Bridging these gaps requires an integrated assessment of cognitive and emotional learning outcomes in the context of the use of educational technology.

In this regard, the present study examines the effect of educational technology on the cognitive and emotional learning outcomes of students in higher education. Specifically, the effects of educational technology engagement on the cognitive outcomes represented by academic performance indicators and the effects of technology-related experiences, including technostress and online learning misfit, on the emotional outcomes represented by learning satisfaction and learning motivation are examined. This study aims to provide a more holistic view of the effects of educational technology on student learning experiences and achievement within today's higher education contexts by doing so.

2. Methodology

2.1 Research Design

The study adopted a quantitative secondary data analysis design to study the effect of educational technology related factors on cognitive and emotional learning outcomes. The analysis merged two independent educational data sources to measure different aspects of student learning. Cognitive outcomes were measured by academic achievement indicators . Emotional outcomes were measured by students' perceptions of technostress, online learning experience, satisfaction, and motivation . In the design, the effects of educational technology were analysed over complementary learning domains by using available empirical data.

2.2 Data Source

The cognitive learning outcome data were collected from an educational dataset published by Najem et al. (2025) and publicly available. The dataset contains student academic performance records and learning engagement indicators in relation to technology-supported learning activities. Following preprocessing, 326 student observations were retained for analysis. The data for emotional learning outcomes were obtained from a publicly available survey dataset of undergraduate students in technology-enhanced learning environments (Nguyen et al., 2026). The dataset measures online learning misfit, technostress, perception of academic performance, learning satisfaction, and learning motivation. After data screening and deletion of duplicates, the analysis was based on 1,317 valid observations.

2.3 Data Preparation

The two datasets were processed in different ways, as they represent different dimensions of learning and different measurement structures. For the cognitive dataset, identifiers were stripped of and categorical variables were converted to numerical variables for analysis. Ordinal academic performance categories and educational technology engagement measures were coded preserving their original rank structure. Duplicate responses were removed from the emotional dataset prior to analysis. Then, the composite construct scores were computed by averaging the corresponding measurement items for technostress, online learning misfit, academic performance, learning satisfaction, and learning motivation. Variables with no variation between observations were excluded from further analysis. The initial assessment suggested that neither of the datasets had any missing values.

2.4 Measures

Cognitive learning outcomes were measured by students' overall grade point average and course completion status. Educational technology engagement reflected indicators related to online learning participation, content interaction, video engagement, and learning activity segmentation. Learning outcomes for emotional learning were learning satisfaction and motivation for learning. The explanatory variables were technostress and online learning misfit which are the perceptions of students concerning technological demands and the extent of the fit between learner characteristics and technology-enhanced learning environments.

2.5 Reliability Assessment

The internal consistency of emotional learning constructs was evaluated using Cronbach's alpha. Reliability analysis was performed for technostress, online learning misfit, academic performance, learning satisfaction, and learning motivation before regression modelling. The obtained coefficients were above the recommended threshold for acceptable reliability, thus supporting the use of composite scores in subsequent analyses.

2.6 Data Analysis

Descriptive statistics were used to summarise the characteristics of the study variables. Then, the Pearson correlation analysis was performed to investigate the associations between educational technology indicators and learning outcomes. Cognitive learning outcomes were tested using logistic regression, with course completion status as the dependent variable. An additional ordinary least squares regression model was estimated, using cumulative grade point average, in order to test the robustness of the findings. To investigate emotional learning outcomes, ordinary least squares regression models were estimated with learning satisfaction and learning motivation as dependent variables. In both models, technostress and online learning misfit were included as explanatory variables. Statistical significance was assessed at the 0.05 level and confidence intervals were computed to aid interpretation of estimated effects.

3. Results

3.1 Descriptive Statistics of Cognitive and Emotional Learning Outcomes

The descriptive statistics showed significant differences among the cognitive and emotional learning outcome datasets. The pass rate of the assessed courses in the cognitive dataset was relatively high ($M = 0.81$, $SD = 0.39$), with most students passing. The average CGPA was 2.25 ($SD=1.17$) suggesting a moderate academic achievement in the sample. In the emotional dataset, the mean scores for Technostress ($M = 3.14$, $SD = 0.93$), Misfit ($M = 2.93$, $SD = 1.00$), Satisfaction ($M = 2.93$, $SD = 1.04$), and Motivation ($M = 2.87$, $SD = 1.07$) were around the middle of the measurement scale, indicating moderate perceptions of technology-related learning experiences. Table 1 presents descriptive statistics for all study variables to be used in the subsequent analyses.

Table 1. Descriptive Statistics of Cognitive and Emotional Learning Outcomes

Dataset	Variable	N	Mean	SD	Minimum	Median	Maximum
Cognitive Outcome	CGPA	326	2.252	1.168	0.000	2.000	5.000
Cognitive Outcome	Result	326	0.810	0.393	0.000	1.000	1.000
Emotional Outcome	Technostress	1317	3.140	0.928	1.000	3.000	5.000
Emotional Outcome	Misfit	1317	2.927	1.000	1.000	3.000	5.000
Emotional Outcome	Performance	1317	2.881	1.021	1.000	3.000	5.000
Emotional Outcome	Satisfaction	1317	2.934	1.037	1.000	3.000	5.000
Emotional Outcome	Motivation	1317	2.872	1.071	1.000	3.000	5.000

3.2 Correlation Structure of Educational Technology Variables and Learning Outcomes

Correlation analysis revealed significantly different patterns in the cognitive and emotional domains. Correlations between indicators of engagement with educational technology and academic outcomes in the cognitive data set were generally weak. For example, CGPA had little relationship with Online C (r = -0.01), Online O (r = 0.00), Played (r = -0.06), Segment (r = -0.03). Similarly, the pass–fail outcome showed only weak relationships with technology engagement indices. On the other hand, the emotional learning constructs were consistently positively correlated. The Technostress was significantly correlated with Misfit (r = 0.76), whereas Satisfaction was highly associated with Motivation (r = 0.85). Performance also had a strong positive relationship with both Satisfaction (r = 0.80) and Motivation (r = 0.80) suggesting a significant interdependence between emotional and technology-related learning constructs. The correlation structure between cognitive outcomes and educational technology engagement variables is shown in Figure 1.

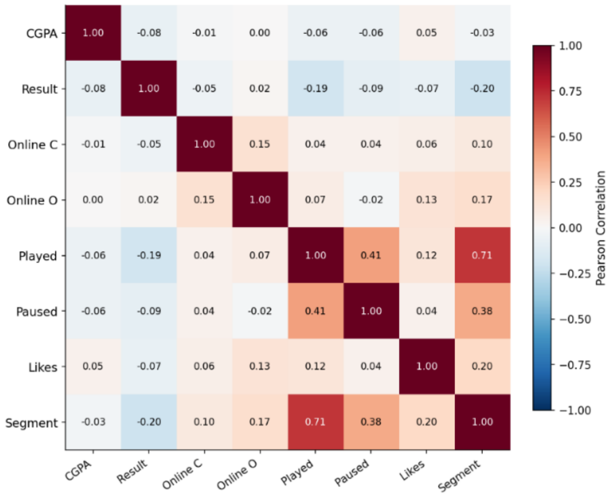

Figure 1. Correlation Structure of Cognitive Outcomes and Educational Technology Engagement

3.3 Reliability of Measurement Constructs

The internal consistency reliability was high for all latent constructs included in the emotional learning dataset. The Cronbach's alpha coefficients ranged from 0.850 to 0.916 which is well above the recommended cut-off point of 0.70. Learning Motivation showed the highest reliability (α = 0.916), followed by Learning Satisfaction (α = 0.895) and Online Learning Misfit (α = 0.888). These findings suggested that the measurement scales had adequate psychometric properties and were appropriate for subsequent regression analyses. Table 2 presents the reliability statistics of all constructs.

Table 2. Reliability Analysis of Emotional Learning Constructs

Construct	Items	Number of Items	Cronbach's Alpha
Technostress	TS1, TS2, TS3	3	0.850
Online Learning Misfit	MF1, MF2, MF3	3	0.888
Academic Performance	PE1, PE2, PE3	3	0.870
Learning Satisfaction	SAT1, SAT2, SAT3	3	0.895
Learning Motivation	MO1, MO2, MO3	3	0.916

3.4 Effects of Educational Technology on Cognitive and Emotional Learning Outcomes

The regression analyses revealed opposite results for cognitive and emotional outcomes. For cognitive learning outcomes, the logistic regression model predicting student success (Result) was statistically significant overall (LLR $p = .015$), but no individual educational technology variable was significant at the conventional 5% level. Segment had a borderline effect (OR = 0.835, $p = 0.094$). The robustness analysis with CGPA as the dependent variable was non-significant ($R2 = 0.008$, $p = 0.852$), indicating that the variables of engagement in educational technology accounted for little variation in academic achievement. In contrast, emotional learning outcomes were found to have large effects. The Satisfaction model accounted for 58.3% of the variance ($R2 = .583$), with both Technostress ($\beta = .283$, $p < .001$) and Misfit ($\beta = .573$, $p < .001$) as significant positive predictors. Similar to this, the Motivation model explained 54.9% variances ($R2 = 0.549$), where Technostress ($\beta = 0.305$, $p < 0.001$) and Misfit ($\beta = 0.557$, $p < 0.001$) had significant positive effects. These results indicate that technology-related learning experiences tend to have a much more pronounced impact on students' emotional outcomes than on their cognitive outcomes. Table 3 shows the regression coefficients, confidence intervals and effect estimates for the cognitive and emotional outcome models

Table 3. Regression Models Predicting Cognitive and Emotional Learning Outcomes

Model	Predictor	Coefficient	Effect Estimate	p-value
Cognitive Outcome: Result	Online C	-0.075	OR = 0.928	0.470
Cognitive Outcome: Result	Online O	0.093	OR = 1.098	0.311
Cognitive Outcome: Result	Played	-0.116	OR = 0.890	0.300
Cognitive Outcome: Result	Paused	0.014	OR = 1.014	0.808
Cognitive Outcome: Result	Likes	-0.125	OR = 0.883	0.403
Cognitive Outcome: Result	Segment	-0.181	OR = 0.835	0.094
Learning Satisfaction	Technostress	0.283	β = 0.283	<0.001
Learning Satisfaction	Misfit	0.573	β = 0.573	<0.001

Learning Motivation	Technostress	0.305	β = 0.305	<0.001
Learning Motivation	Misfit	0.557	β = 0.557	<0.001

To further illustrate the magnitude of the effects of the emotional outcome, predicted values from the regression models are shown in Figure 2. Figure 3 shows the comparative effect sizes of Technostress and Online Learning Misfit in models of emotional outcomes.

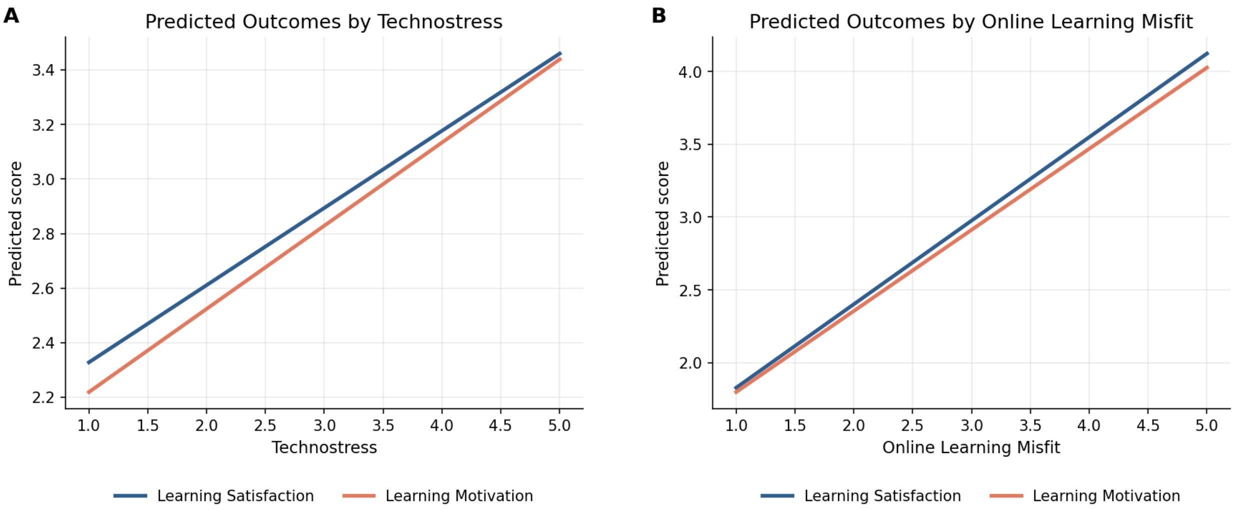

Figure 2. Predicted Emotional Learning Outcomes. (A) Predicted Satisfaction Across Levels of Technostress and Misfit. (B) Predicted Motivation Across Levels of Technostress and Misfit

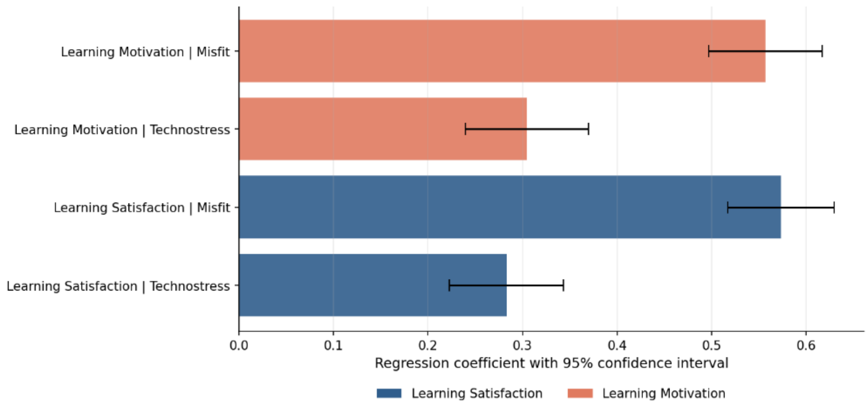

Figure 3. Regression Effect Estimates of Technology-Related Factors on Emotional Learning Outcomes

The results show that the educational technology engagement variables have low explanatory power for the cognitive outcomes, while the technology-related learning experiences, especially the online learning misfit and technostress, have high and statistically significant relationships with the emotional learning outcomes. Such divergence suggests that educational technology may have its strongest impact on students' perceptions, attitudes and motivational states rather than directly on measurable academic performance.

4. Discussion

The results indicate a significant difference between the cognitive and emotional aspect of learning in technology enhanced education. Engagement indicators of educational technology had weak explanatory power for cognitive learning outcomes. The logistic regression model predicting course result was statistically significant at the model level but no individual technology engagement variables were statistically significant at conventional levels. The supplementary model with CGPA as cognitive outcome has also negligible explanatory power. This pattern suggests that online participation and content interaction variables alone may not be sufficient to account for academic achievement measured by technology engagement. A wider set of academic, instructional, motivational and contextual conditions is likely to influence cognitive performance, but these were not fully captured in the cognitive dataset.

The emotional outcome models, the more so, showed a stronger and more consistent pattern. Technostress and online learning misfit were significant predictors of learning satisfaction and learning motivation. The explained variance was substantial, suggesting that students' emotional responses to technology-enhanced learning are highly related to their experience of technological demands and the alignment between learning demands and personal capacities. Caution is needed in interpreting the positive direction of these associations. Rather than implying that stress or misfit is desirable in and of itself, the findings may simply reflect students' greater sensitivity to the challenges of technology-mediated learning in active digital learning environments. Students who are more involved in such environments may report higher perception of technostress and misfit and higher motivation and satisfaction. Overall, the findings imply that educational technology may more directly affect students' emotional and perceptual learning outcomes than their measured academic outcomes. Digital learning tools can influence students' feelings, adjustment, perseverance, and evaluation of their learning environment, even when these effects do not appear immediately in grades or completion outcomes. This distinction is important because emotional learning outcomes often precede cognitive gains . Satisfaction and motivation can promote persistence, engagement, and self-regulation, but the association with academic performance may be contingent upon time, quality of instruction, and adequate learning design. The weak cognitive findings are partially consistent with research suggesting that technology-related factors do not necessarily translate into better academic achievement. Hanham et al. (2021) argued that technology acceptance and academic self-efficacy influence academic achievement in online tutoring settings, thus technology use alone is not likely to lead to performance improvement without learner confidence and acceptance. Likewise, Cudris-Moreno et al. (2020) demonstrated that educational technology and academic performance in emergency digital learning were conditioned by broader learning conditions, proving that digital access does not always lead to better academic outcomes. The emotional findings are supported by research that has demonstrated a positive association between technology-enhanced learning and student satisfaction and motivational experiences . Alyoussef and Omer (2023) found that satisfaction and adoption are central to students' experiences of technology-enhanced learning in higher education. Liang et al. (2024) also found that the integration of technology-enhanced learning is associated with performance, satisfaction, and motivation, supporting the idea that educational technology influences many facets of the student experience. The strong role of technostress and online learning misfit also echoes with work highlighting the psychological challenges of digital learning . Nurlela et al. (2025) underlined the importance of psychosocial support to assist students and lecturers in overcoming the challenges of digital education. Furthermore, Selvanathan et al. (2023) demonstrated that students' learning experiences were influenced by environmental and personal adjustment factors during remote learning, supporting the importance of learner–environment alignment. Research on engagement also supports a broader interpretation of emotional outcomes. Venn et al. (2023) argue that learning technologies impact both emotional and cognitive engagement but these types of engagement may not work in the same way. Şahin et al. (2022) found important emotional outcomes related to the adoption of e-learning during compulsory online education, supporting the current finding that technology-enhanced learning is strongly associated with satisfaction and motivation. The findings have important implications for theory and practice. In principle, the study underlines that learning outcomes should be addressed as multidimensional, rather than assuming that the effectiveness of technology should only be assessed by academic performance. Technology-related factors seem to have different effects on cognitive and emotional outcomes. The emotional outcomes may be more sensitive to students' immediate experiences with digital learning environments than the cognitive outcomes, which may be dependent on other instructional and academic variables. The direction of the coefficients should be interpreted in relation to the original survey coding scheme used to construct the composite variables. In practice, educational technology should be evaluated by higher education institutions not only based on grades or completion rates, but also on students' satisfaction, motivation, and perceived fit with the digital learning requirements. Access to platforms is not enough to effectively integrate technology. Students require clear guidance, realistic digital workloads, responsive technical support and learning designs that match technological demands with the capabilities of learners. Instructors should be sensitive to the signs of technostress and misfit as these experiences are strongly associated with affective learning outcomes. The findings also indicate the need for educational technology policies to include emotional learning indicators in quality assurance. Student motivation and satisfaction can be early indicators of whether technology enhanced learning environments are supportive, usable and sustainable. Schools that depend solely on performance indicators may neglect the important affective conditions that affect students' long-term engagement.

Some limitations should be acknowledged. The analysis was conducted on secondary datasets and the cognitive and emotional outcomes were obtained from different student samples. This makes it difficult to compare the two outcome domains directly. The study was cross-sectional so causal interpretation is limited. Further, the emotional variables were based on self-reported responses, which may be more reflective of students' perceptions than of observed behaviour. Future studies should explore cognitive and emotional learning outcomes within the same student population. Longitudinal designs would be useful to determine whether emotional responses to educational technology ultimately lead to academic improvement. Additional research could incorporate the analysis of instructional quality, previous achievement, digital competence and logs of platform usage to design a more complete model of the influence of educational technology on learning outcomes.

5. Conclusion

Educational technology had a differential impact on student learning outcomes. The explanatory power for cognitive outcomes was limited, as technology engagement indicators were not significant predictors of CGPA or individual pass–fail performance. On the contrary, technology-related learning experience was significantly associated with emotional outcomes, especially learning satisfaction and motivation. Technostress and misfit with online learning showed a significant predictive effect, suggesting that students' affective reactions to digital learning contexts are significantly associated with perceptions of technological demands and learner-environment fit. These results suggest that the effectiveness of educational technology should not be judged solely by measures of academic performance. Emotional outcomes provide valuable insights into students' adaptation, motivation and satisfaction in technology enhanced learning settings. This means that higher education institutions should develop digital learning environments that are accessible, interactive, psychologically supportive and matching students' capabilities. Future research should also consider cognitive and emotional outcomes in the same population of students to better understand how emotional responses to educational technology may help contribute to academic improvement over time .

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