

PAPER

Online Learning Self-Efficacy, AI Anxiety, and Digital Well-Being in Engineering Students: A Predictive Model

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ABSTRACT

This study investigates the relationships among online learning self-efficacy (OLSE), artificial intelligence anxiety (AIA), and digital well-being (DWB) among undergraduate engineering students from six Jordanian universities (N = 428). Using validated self-report measures and a cross-sectional design, descriptive results indicated moderate OLSE (M = 3.24), moderately high AIA (M = 3.97), and moderate-to-low DWB (M = 2.41). A hypothesized mediation model was supported: OLSE was negatively associated with AIA ($\beta = -0.64$, $p < .001$) and positively associated with DWB ($\beta = 0.52$, $p < .001$), while AIA was negatively associated with DWB ($\beta = -0.33$, $p < .001$). The indirect effect of OLSE on DWB through reduced AIA was significant ($\beta = 0.21$, 95% CI [0.12, 0.34]), indicating partial mediation. The final model explained 76% of the variance in DWB. These findings highlight the importance of efficacy-building and AI-literacy supports to reduce AI-related anxiety and promote sustainable DWB in AI-enabled engineering education.

KEYWORDS

online learning self-efficacy (OLSE), artificial intelligence anxiety (AIA), digital well-being (DWB), engineering education

1 INTRODUCTION

The integration of artificial intelligence (AI) and digital learning platforms has reshaped engineering education by enabling more interactive, adaptive, and flexible learning experiences aligned with Industry 4.0 paradigms [1], [2]. These technologies support automated feedback, personalized content delivery, and simulation-based learning that enhance cognitive engagement and skill transfer among engineering students [3], [4]. Yet this pedagogical transformation is not without psychological cost—students increasingly report stress, information overload, and anxiety within AI-mediated learning environments [5], [6]. As learners spend more time interacting with digital interfaces, digital well-being (DWB)—defined as balanced

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and mindful engagement with technology that sustains emotional stability and learning efficiency—has become a crucial dimension of academic success [7], [8]. Conversely, poor digital well-being, often linked to excessive screen exposure and weakened self-regulation, can undermine concentration, creativity, and academic resilience [9], [10]. In the Jordanian higher-education context, engineering students face additional pressures as they navigate rapid digital transformation while preparing for AI-driven labor markets where institutional and infrastructural readiness remain uneven [3], [11]. Understanding how online learning self-efficacy (OLSE) and AI-related anxiety jointly shape DWB can therefore guide evidence-based strategies to foster psychological stability and technological adaptability among future engineers [8], [12].

2 LITERATURE REVIEW

2.1 DWB

Digital well-being refers to the emotional, behavioral, and cognitive regulation of technology use in ways that sustain learning performance and mental health [7], [8]. Empirical research shows that students with stronger digital self-control, greater digital literacy, and higher perceived control report greater DWB and academic satisfaction [9], [10]. Conversely, excessive screen time, multitasking across platforms, and constant notifications—and the resulting information overload—are consistently associated with higher stress, fatigue, and diminished learning outcomes [8], [11]. Within engineering programs, where students routinely engage in coding, simulations, and online laboratories, DWB acquires particular relevance. The design of digital tools, interface ergonomics, and institutional support can either mitigate or intensify digital fatigue and cognitive overload [2], [12]. Promoting DWB therefore forms a foundational element of curricula that incorporate AI-based instructional tools [1], [8].

2.2 AI anxiety

Artificial intelligence anxiety (AIA) refers to the apprehension or fear linked to artificial intelligence, automation, and their perceived implications for learning, employability, and human agency [5], [6]. Recent studies show that students who perceive AI as a potential threat or feel unprepared for AI-mediated learning tasks experience higher anxiety, which in turn reduces engagement with AI-supported tools [3], [12]. For instance, Russo et al. [12] highlighted the role of AIA in shaping attitudes toward AI and reported gender-related differences in these relationships. Similarly, Chen et al. [13] demonstrated in a Chinese sample ($n = 387$) that AI self-efficacy moderates the relationship between AIA and motivated learning: when self-efficacy is high, the negative impact of anxiety diminishes [13]. In the context of engineering education—where AI-based systems are increasingly embedded—addressing AIA is essential for encouraging students to adopt and benefit from AI-integrated pedagogies [4], [6].

2.3 OLSE

Grounded in Bandura's (1997) self-efficacy theory, OLSE refers to students' beliefs in their capability to organize, manage, and succeed within digital learning

environments [15]. Higher OLSE correlates with improved academic achievement, stronger motivation, and lower dropout rates in online settings [3], [15]. Previous studies have shown that students with higher OLSE use digital platforms more effectively, manage time efficiently, and persist through technical or academic challenges [15], [28]. Foundational work also shows that OLSE is multi-dimensional (e.g., course completion, social interaction, LMS/tool use, and instructor/classmate interaction) and predicts students' online learning satisfaction [16]. In AI-supported learning environments, OLSE may buffer the negative effects of AIA and low digital well-being, helping students adapt to emerging technological demands [1], [8]. Given this pivotal role, OLSE has been theorized as a key antecedent linking technological demands with psychological adjustment and learning success [15], [16].

2.4 Previous studies

Prior investigations into the interplay among digital well-being, AI anxiety, and OLSE indicate complex and sometimes bidirectional relationships. Neagu [29] reported robust associations between digital and psychological well-being (e.g., autonomy and mastery) among students enrolled in technical academic programs. Other recent work similarly suggests that stronger DWB is associated with fewer technology-related concerns and more adaptive engagement in digitally intensive learning settings [2], [11].

Broader policy and institutional evidence further indicate that digitalization can produce mixed effects on student well-being, underscoring the importance of pedagogical designs that mitigate overload, promote healthy technology-use routines, and support self-regulation [18], [19]. Consistent with this perspective, digital fatigue and information overload have been linked to elevated technology-related apprehension and diminished academic functioning. Alfathyah et al. [11], for example, documented that poorer digital well-being—particularly fatigue and overload—was associated with adverse outcomes among engineering undergraduates. Large-scale work also links heavy screen exposure with heightened stress and mental-health symptoms among university students, reinforcing the mechanism through which degraded DWB may impair attention and learning engagement [9], [10].

Within the AI-anxiety domain, Wang and Wang [14] developed and validated the AIAS Scale, providing evidence of its construct validity and relevance for learning-related outcomes. Subsequent empirical studies consistently show that AIA is inversely associated with AI literacy, positive attitudes toward AI, and readiness to engage with AI-enabled learning tasks [12], [13]. Recent syntheses further position anxiety—alongside motivational and dependency-related dimensions—as a key psychological factor shaping AI adoption and engagement in higher education [6], [20].

Parallel research highlights OLSE as a protective factor in online and technology-enhanced learning. Foundational evidence indicates that OLSE is multidimensional—encompassing course management, interaction, and digital-tool use—and predicts satisfaction and persistence in online learning environments [16].

Additional work supports the role of self-efficacy and self-regulation as central mechanisms underlying successful online learning adaptation and continued engagement, particularly under high digital demands [26], [28]. In Middle Eastern contexts, evidence suggests that uneven institutional readiness can amplify technology-related anxiety and reduce effective system use when scaffolding and support are limited. In Jordan specifically, Alkhawaja [21] showed that technology anxiety negatively affected actual e-learning system use in public universities, supporting the

need for interventions that build efficacy and reduce apprehension. Sectoral and policy reports similarly emphasize variability in institutional digital capacity during rapid transformation, strengthening the case for integrative research on well-being, anxiety, and efficacy in Jordanian higher education [22].

Despite these contributions, prior work has not yet empirically tested the proposed tri-construct model—digital well-being, AI anxiety, and OLSE—within a single framework among engineering students in Jordan, where rapid digitalization and variable institutional readiness may create distinctive psychological pressures [3], [21], [22].

3 METHODOLOGY

3.1 Research design

This study employed a descriptive–correlational, cross-sectional design, which is appropriate for examining predictive relationships among psychological and behavioral constructs in higher-education settings. Quantitative data were collected using validated self-report instruments administered to undergraduate engineering students enrolled in Jordanian universities. This design supports estimating associations among key variables and testing theory-driven mediation pathways using regression and structural equation modeling (SEM) approaches commonly used in educational and psychological research [25], [33]. The conceptual framework was grounded in Bandura’s self-efficacy theory, which emphasizes that perceived capability influences individuals’ emotional reactions, persistence, and adaptive functioning under challenging learning demands [15]. In technology-intensive learning contexts, prior evidence suggests that students’ technology-related well-being and adaptation are shaped by both institutional digital conditions and students’ personal resources such as self-efficacy and self-regulation [18], [19], [26].

3.2 Participants

The target population comprised undergraduate engineering students from six major Jordanian universities representing both public and private sectors. Departments included Computer, Communications, Electrical, Mechatronics, and Biomedical Engineering, reflecting the diversity of technological exposure and disciplinary specialization across Jordan’s higher education system [2], [4]. A stratified sampling approach was used to ensure representation across institutions and key demographic groups. Within each stratum (university \times program), participants were recruited through voluntary online participation via official mailing lists and student groups. After screening, 428 valid responses were retained (52.1% male, 47.9% female; $M = 21.3$ years, $SD = 1.6$), consistent with age distributions reported in comparable higher-education samples [8]. Eligibility criteria required participants to: (a) be enrolled in at least one online or blended engineering course, and (b) have prior exposure to AI-integrated or LMS-supported tools (e.g., automated grading, adaptive quizzes, AI tutoring systems, or plagiarism-detection platforms). These criteria ensured meaningful contact with the psychological constructs under investigation, particularly technology-related anxiety and OLSE [11], [21]. The sampling rationale is aligned with regional evidence highlighting variability in institutional digital readiness and the potential impact of technology anxiety on students’ engagement in Jordanian higher education [21], [22].

3.3 Instruments

Three psychometrically validated scales were used to assess digital well-being, AI anxiety, and OLSE.

DWB. Digital well-being was assessed using an 18-item adapted measure designed to capture balanced technology engagement, emotional stability, and behavioral self-regulation in digital learning. Item content was mapped to established conceptual and policy frameworks on DWB in education [11], [18], [19], [34]. Responses were recorded on a five-point Likert scale (1 = strongly disagree to 5 = strongly agree). In engineering contexts, digital fatigue and overload were treated as relevant facets due to intensive use of simulations, coding, and online platforms.

AIA. AI anxiety was measured using the AIAS Scale developed and validated by Wang and Wang [14]. The scale assesses cognitive unease, emotional apprehension, and behavioral avoidance related to AI technologies and their implications for learning and performance. It has been widely positioned as suitable for technology-enhanced learning contexts where AI-related concerns can shape motivation and engagement [12], [13], [20].

OLSE. Online learning self-efficacy was assessed using a 20-item scale measuring students' confidence in managing online learning tasks, including communication, course management, digital-resource use, and self-regulated learning strategies. The construct is grounded in self-efficacy theory [15] and supported by foundational work demonstrating that OLSE predicts satisfaction and persistence in online learning [16]. Complementary evidence highlights the interdependence of self-efficacy and self-regulation in successful online learning adaptation [26], [28]. All instruments underwent expert review by ten academics to evaluate content relevance and linguistic clarity. A pilot test ($n = 30$) supported internal consistency and stability (Cronbach's α and McDonald's $\omega > .80$; test-retest coefficients $> .75$), indicating adequate reliability for use in the main study, consistent with standard guidance for psychometric use in behavioral research [25].

3.4 Procedure

Ethical approval was obtained from the Institutional Review Board (IRB #2025/1/12) of the lead university. Participants provided informed consent electronically, with emphasis on voluntariness, anonymity, and the right to withdraw at any time. Data were collected via an online questionnaire distributed between April and June 2025 through student mailing lists and official university groups. Built-in validation rules were used to reduce missing responses and duplicate submissions. Cases with more than 10% missing data were removed during screening. Descriptive statistics were computed, and internal consistency was reconfirmed prior to model testing. Univariate distribution checks indicated acceptable levels for parametric analysis assumptions (skewness < 2 ; kurtosis < 7), aligning with commonly cited SEM practice guidelines [24], [25].

3.5 Data analysis

The primary aim of the data analysis was to examine the direct and indirect relationships among the three constructs and to test the hypothesized mediation model. Data were analyzed using SPSS (v.29) and AMOS (v.27) following a multi-stage

analytic procedure. Preliminary diagnostics were conducted to ensure compliance with statistical assumptions, including linearity, normality, and multi-collinearity. Given the high bivariate associations among constructs, collinearity was considered at the model-estimation stage. Interpretation therefore relied on the stability of standardized coefficients across the observed-score OLS regression and the latent-variable SEM, as well as the bootstrapped confidence intervals for structural paths, rather than on bivariate correlations alone. Descriptive statistics and Pearson correlations were first computed to examine bivariate relationships among OLSE, AI anxiety, and DWB [25]. To test the hypothesized mediation mechanism, an SEM approach was employed in AMOS. The model specified that OLSE predicts AI anxiety, which subsequently predicts DWB. A direct path from OLSE to DWB was also included to evaluate partial mediation. Model estimation used the maximum-likelihood (ML) method with bias-corrected bootstrap resampling (5,000 samples; 95% confidence intervals) to assess the significance of indirect effects and ensure robust standard errors [25]. Model fit was evaluated using commonly reported guidelines for χ^2/df , CFI, TLI, RMSEA, and SRMR (e.g., CFI/TLI around .90–.95, RMSEA \leq .06–.08, and SRMR \leq .08), interpreted holistically rather than via a single strict cutoff [23], [24]. The statistical significance level was set at $\alpha = .05$, and both direct and indirect effects were interpreted within the theoretical framework of Bandura's Social Cognitive Theory [15]. Overall, model fit was good to excellent. While some indices (e.g., TLI) were marginally below the most stringent cutoff, the full set of indices (CFI, RMSEA, SRMR, and χ^2/df) supported an acceptable-to-good fit for both the measurement and structural models, providing a solid foundation for testing the hypothesized relationships presented in Section 4.

The data analysis followed the rigorous two-step approach recommended by Anderson and Gerbing [32]. In the first step, a pooled measurement model was evaluated through Confirmatory Factor Analysis (CFA) to verify the psychometric properties of all latent constructs simultaneously (OLSE, AI Anxiety, and DWB), consistent with recommendations for assessing measurement quality in multi-construct models [25], [33]. In the second step, the structural equation model (SEM) was estimated using the maximum likelihood (ML) method in AMOS v.27. To ensure the robustness of the indirect effects, bias-corrected bootstrapping with 5,000 resamples was employed to generate 95% confidence intervals [33].

4 RESULTS

The results of this study are presented in accordance with the three research questions, beginning with descriptive statistics and followed by correlational, regression, and structural equation analyses. The data were analyzed using SPSS v.29 for preliminary statistics and AMOS v.27 to test the hypothesized structural model. The direction of relationships was based on the conceptual model proposing that OLSE reduces AIA, which in turn enhances DWB, with AIA partially mediating this relationship.

4.1 Descriptive statistics

Table 1 displays the mean scores and standard deviations for the three core variables. The findings indicate that students reported moderate OLSE ($M = 3.240$, $SD = 1.364$), moderately high AIA ($M = 3.974$, $SD = 1.603$), and moderate-to-low DWB

($M = 2.409$, $SD = 1.243$) on a five-point Likert scale. These descriptive results reflect a learning environment where students demonstrate a fair level of confidence in online education but also experience substantial anxiety regarding AI, which appears to impact their digital balance and well-being.

Table 1. Descriptive statistics for key study variables ($N = 428$)

| Variable | Mean (M) | Standard Deviation (SD) | Scale Range | Level Interpretation |
|------------|----------|-------------------------|-------------|----------------------|
| OLSE | 3.240 | 1.364 | 1–5 | Moderate |
| AI Anxiety | 3.974 | 1.603 | 1–5 | Moderately High |
| DWB | 2.409 | 1.243 | 1–5 | Moderate to Low |

The observed pattern implies that although students are somewhat competent in managing online learning platforms, their psychological adjustment to AI technologies remains limited. The moderate-to-low levels of DWB suggest that technological engagement might be accompanied by fatigue, information overload, and decreased emotional balance—conditions that align with prior international research on technostress and digital burnout in higher education contexts.

4.2 Correlation analysis

To investigate the relationships among the study variables, Pearson correlation coefficients were calculated. As shown in Table 2, OLSE was found to correlate negatively with AIA ($r = -0.886$, $p < .001$), indicating that students with higher confidence in online learning experience less anxiety toward AI. AIA was also negatively correlated with DWB ($r = -0.853$, $p < .001$), suggesting that elevated anxiety is associated with poorer DWB. Conversely, OLSE and DWB demonstrated a strong positive correlation ($r = 0.919$, $p < .001$), implying that students who are more self-efficacious in managing their learning environments report healthier and more balanced digital lifestyles [25].

Table 2. Pearson correlations among OLSE, AIA, and DWB ($N = 428$)

| Variable | 1 | 2 | 3 |
|---------------|----------|----------|---|
| 1. OLSE | – | – | – |
| 2. AI Anxiety | –0.886** | – | – |
| 3. DWB | 0.919** | –0.853** | – |

Note: ** $p < .001$ (two-tailed).

These correlation patterns align with the theoretical assumptions of the model, emphasizing that OLSE operates as a protective factor against anxiety related to AI and plays a central role in promoting DWB among engineering students. Although the correlations among the constructs were high, interpretation did not rely on bivariate associations alone. Instead, the stability of coefficients across the observed-score regression and latent-variable SEM, together with bootstrapped confidence intervals, was used to support that predictors retained sufficient unique variance for stable estimation. Notably, the strong correlations reflect substantial shared

variance (e.g., $r^2 \approx 0.85$ between OLSE and DWB), which is theoretically expected in mediation models where predictors and outcomes are conceptually proximal yet retain distinct roles within the causal structure. Proximity at the bivariate level does not imply redundancy; the measurement-model evidence and the significance of the mediated pathway support treating the constructs as related but distinct.

4.3 Regression analysis

To assess the predictive influence of OLSE and AIA on digital well-being, a multiple regression analysis was conducted. *The model was statistically significant, $F(2, 425) = 1213.67$, $p < .001$, and explained 85.1% of the variance ($R^2 = 0.851$) in DWB.* As reported in Table 3, OLSE was a strong positive predictor ($\beta = 0.755$, $p < .001$), while AIA was a significant negative predictor ($\beta = -0.185$, $p < .001$).

Table 3. Multiple regression predicting DWB (N = 428)

| Predictor | B | SE | Beta (β) | t | Sig. |
|--|--------|-------|------------------|--------|--------|
| (Constant) | 0.752 | 0.274 | – | 2.742 | .006 |
| OLSE | 0.688 | 0.042 | 0.755 | 16.201 | < .001 |
| AI Anxiety | –0.144 | 0.036 | –0.185 | –3.979 | < .001 |
| Model Summary: $F(2, 425) = 1213.67$, $p < .001$, $R^2 = 0.851$, Adj. $R^2 = 0.849$ | | | | | |

The findings, based on the full sample of 428 engineering students, demonstrate that those who exhibit greater confidence in managing online learning platforms also maintain stronger emotional balance and healthier digital habits. Conversely, higher anxiety toward AI technologies was associated with lower levels of digital well-being. This robust predictive pattern suggests that strengthening OLSE remains one of the most effective strategies for promoting digital wellness in AI-driven academic environments.

Before assessing the structural pathways, the full measurement model was evaluated through CFA [25], [33]. The results indicated an excellent fit for the hypothesized three-factor model: $\chi^2/df = 2.14$, CFI = 0.958, TLI = 0.944, RMSEA = 0.046, and SRMR = 0.039 [23], [24]. All standardized item loadings were statistically significant ($p < .001$) and ranged from 0.74 to 0.92, exceeding the recommended 0.70 threshold. Discriminant validity was examined using the Fornell–Larcker criterion. Given the very strong association between OLSE and DWB ($r = .919$), the Fornell–Larcker results were interpreted cautiously. While \sqrt{AVE} for DWB (0.927) exceeded the inter-construct correlation, \sqrt{AVE} for OLSE (0.916) was marginally lower than r , indicating close empirical proximity between these constructs in this sample. It should be noted that the Fornell–Larcker criterion is known to be conservative and may underestimate discriminant validity when constructs are theoretically related and highly reliable. In line with recent recommendations, future studies may complement this assessment using alternative criteria such as the Heterotrait–Monotrait ratio (HTMT), particularly when examining closely related psychological constructs. Accordingly, discriminant validity evidence was considered alongside (i) the strong overall fit of the measurement model, (ii) substantial and significant standardized loadings, and (iii) the theoretical distinction between perceived capability to manage online learning demands (OLSE) and the affective–regulatory quality of technology use (DWB).

Once the measurement model was evaluated, the hypothesized mediation model—from OLSE to AIA to digital well-being—was examined. The structural model showed an excellent overall fit to the data ($\chi^2/df = 2.05$, CFI = 0.956, TLI = 0.942, RMSEA = 0.045, SRMR = 0.041), as shown in Table 4. Standardized path coefficients indicated that OLSE significantly and negatively predicted AIA ($\beta = -0.64$, $p < .001$), which in turn negatively predicted DWB ($\beta = -0.33$, $p < .001$). Self-efficacy also exerted a significant direct positive effect on DWB ($\beta = 0.52$, $p < .001$), confirming partial mediation. Bootstrapping with 5,000 resamples validated the indirect effect of OLSE on DWB through AIA ($\beta = 0.21$, 95% CI [0.12, 0.34], $p < .001$). [23], [24] The final model explained 41% of the variance in AIA and 76% of the variance in digital well-being. Collectively, these findings indicate that higher OLSE is associated with lower AIA and higher digital well-being, both directly and indirectly.

Table 4. Goodness-of-fit indices for the SEM model

| Fit Index | Obtained Value | Interpretation |
|-----------------------------|----------------|----------------|
| χ^2/df | 2.05 | Good Fit |
| CFI (Comparative Fit Index) | 0.956 | Excellent Fit |
| TLI (Tucker-Lewis Index) | 0.942 | Acceptable Fit |
| RMSEA | 0.045 | Excellent Fit |
| SRMR | 0.041 | Excellent Fit |

Note: Measurement-model (CFA) fit indices are reported in Section 4.3; Table 4 reports the structural-model (SEM) fit.

The results confirmed that the proposed model provided a good-to-excellent representation of the observed data, supporting the hypothesized relationships among self-efficacy, AIA, and digital well-being.

Table 5. Psychometric properties of the latent constructs (N = 428)

| Construct | Items | Loading Range | Cronbach's α | CR | AVE |
|-----------|-------|---------------|---------------------|------|------|
| OLSE | 20 | 0.76–0.91 | 0.94 | 0.95 | 0.84 |
| AIA | 16 | 0.74–0.88 | 0.89 | 0.91 | 0.78 |
| DWB | 18 | 0.74–0.92 | 0.92 | 0.94 | 0.86 |

Note: CR = Composite Reliability; AVE = Average Variance Extracted.

Prior to testing the structural relationships, the psychometric quality of the measurement model was examined. As reported in Table 5, all three latent constructs demonstrated strong internal consistency and convergent validity. Composite reliability (CR) values ranged from 0.91 to 0.95, exceeding the recommended threshold of 0.70, while average variance extracted (AVE) values ranged from 0.78 to 0.86, surpassing the minimum criterion of 0.50. Standardized factor loadings for the observed indicators were substantial, with loading ranges between 0.74 and 0.92 across constructs, indicating that the items reliably represented their intended latent variables. Collectively, these results provide robust evidence that the measurement model exhibits satisfactory convergent validity and reliability for use in subsequent SEM [25].

Structural path coefficients. The standardized regression weights from AMOS indicated statistically significant relationships among all constructs (refer to Table 6).

Table 6. Standardized path coefficients

| Path | Estimate (β) | SE | CR (t) | p-value | Significance |
|--------------------------------------|----------------------|------|--------|---------|--------------|
| OLSE \rightarrow AI Anxiety | -0.64 | 0.05 | -12.80 | < .001 | Sig |
| AIA \rightarrow DWB | -0.33 | 0.04 | -8.25 | < .001 | Sig |
| OLSE \rightarrow DWB (Direct Path) | 0.52 | 0.05 | 10.40 | < .001 | Sig |

These coefficients confirm that higher OLSE significantly reduces AIA and enhances digital well-being. The persistence of the direct path from OLSE to DWB ($\beta = 0.52, p < .001$) even after accounting for AIA suggests partial mediation, where self-efficacy contributes to well-being both directly and indirectly through its mitigating effect on anxiety.

SEM model visualization. The structural equation model generated by AMOS is presented in Figure 1. The diagram displays standardized coefficients for each path, as well as residual variances and model fit indices.

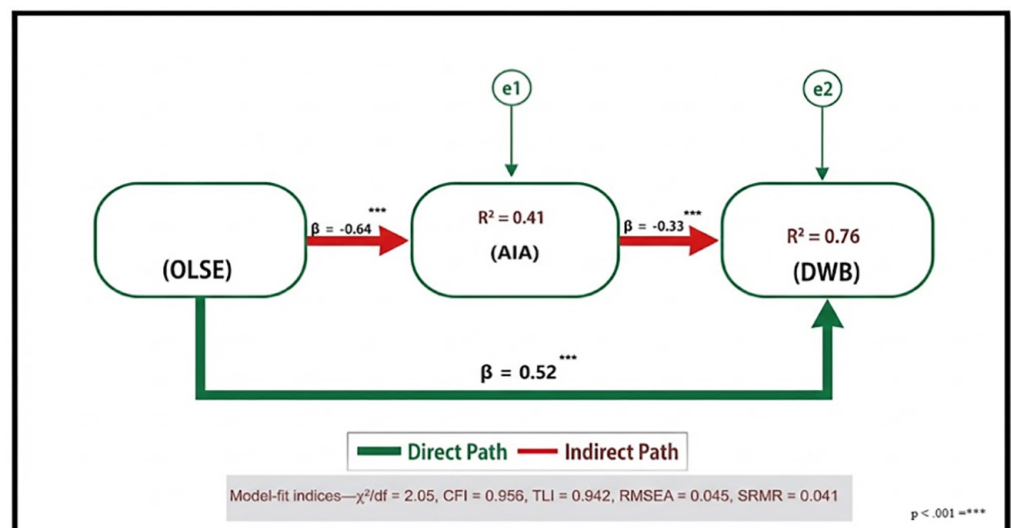


Fig. 1. SEM (AMOS) of OLSE, AIA, and DWB

Latent variables (OLSE, AIA, DWB) are depicted as ellipses, with observed indicators as rectangles. Single-headed arrows represent structural paths; double-headed arrows represent covariance; residuals are shown for endogenous constructs. Figure 1 presents the tested SEM illustrating the predictive and mediating relationships among OLSE, AIA, and DWB. The path diagram was generated directly from the AMOS SEM output based on the observed dataset of $N = 428$ engineering students. All reported coefficients are standardized (β) values derived from the bootstrapped model (5,000 resamples) to ensure stable parameter estimates and robust confidence intervals. Model-fit indices— $\chi^2/df = 2.05$, CFI = 0.956, TLI = 0.942, RMSEA = 0.045, SRMR = 0.041—all meet or approach recommended thresholds [23], [24], [25], confirming an excellent fit between the hypothesized and observed covariance structures. Latent variables (OLSE, AIA, and DWB) are depicted as ellipses, with observed indicators as rectangles. Single-headed arrows represent structural paths; double-headed arrows represent covariance; residuals are shown for endogenous

constructs. Each path is labeled with its standardized coefficient and statistical significance (* $p < .001$).

By grounding the figure in actual AMOS output rather than graphic reconstruction, and by clearly reporting all fit indices and significance levels, the figure provides transparent, replicable evidence that the hypothesized mediation model was statistically validated.

Indirect and total effects. Bootstrapping with 5,000 resamples was used to test the indirect pathway from OLSE to DWB through AI anxiety. The procedure confirmed that the indirect effect was statistically significant, as shown in Table 7.

Table 7. Direct, indirect, and total effects from bootstrapped SEM ($N = 428$)

| Path | Direct Effect (β) | Indirect Effect (β) | Total Effect (β) | 95% CI | Significance |
|-------------------------------|---------------------------|-----------------------------|--------------------------|----------------|--------------|
| OLSE \rightarrow AI Anxiety | -0.64 | - | - | [-0.74, -0.52] | $p < .001$ |
| AIA \rightarrow DWB | -0.33 | - | - | [-0.45, -0.19] | $p < .001$ |
| OLSE \rightarrow DWB | 0.52 | 0.21 | 0.73 | [0.61, 0.83] | $p < .001$ |

The indirect effect ($\beta = 0.21$, 95% CI [0.12, 0.34]) was significant, confirming partial mediation: higher OLSE reduces AIA, which subsequently enhances DWB. This finding reinforces that students with stronger confidence in managing digital learning environments experience less anxiety toward AI and greater overall digital well-being.

4.4 Summary of findings

The findings from both the regression and SEM analyses indicate that OLSE is a key predictor of DWB among engineering and IT students. Higher self-efficacy not only directly fosters more positive and balanced digital learning experiences but also indirectly enhances well-being by reducing anxiety toward AI technologies. The final SEM model explained 76% of the variance in DWB ($R^2 = 0.76$), highlighting the strength and stability of the observed relationships. Collectively, these results emphasize that strengthening students' self-efficacy is essential for promoting healthy psychological adaptation to AI-integrated learning environments in higher education [33].

The strong associations among OLSE, AIA, and DWB reflect their close conceptual proximity within AI-mediated learning environments, where cognitive, emotional, and behavioral dimensions interact. Therefore, the high correlations and explained variance (R^2) are theoretically expected rather than indicative of redundancy, supported by adequate discriminant validity and consistent findings across regression and SEM analyses. However, due to the cross-sectional design, the results should be interpreted as predictive associations rather than causal effects. Future research using longitudinal or experimental designs, along with additional variables such as AI literacy and institutional support, would further strengthen the model.

5 DISCUSSION

This study adds to ongoing discussions surrounding digital transformation and psychological adaptation within engineering education. By integrating evidence

from both regression and structural equation modeling, it confirms that OLSE stands as the primary psychological determinant of engineering students' DWB. Students with higher levels of self-efficacy reported less AI-related anxiety and demonstrated greater emotional balance, emphasizing the protective influence of confidence and perceived competence in technology-intensive learning settings. The close alignment between the theoretical foundation and the empirical data reinforces the view that personal agency remains essential for maintaining psychological well-being in rapidly digitalized learning environments [14], [16], [26].

5.1 Self-efficacy as the central mechanism

Consistent with Bandura's Social Cognitive Theory [15], the findings affirm that self-efficacy beliefs shape how learners interpret and manage challenging digital tasks. In AI-integrated engineering settings, where students often face ambiguous algorithmic grading or automated feedback, uncertainty is a common experience. Those with stronger self-efficacy perceive such challenges as manageable rather than threatening, which reduces anxiety and fosters better well-being. Previous studies have shown that higher self-efficacy enhances motivation, persistence, and the ability to regulate stress in online learning contexts [16], [26], [28]. Recent work in AI-enhanced education further supports this conclusion, showing that students with higher self-efficacy adapt more effectively to algorithmic assessments and display greater emotional resilience [13], [20]. The substantial variance explained in the final model ($R^2 = 0.76$ for DWB) reinforces the role of OLSE not merely as a technical skill but as a primary psychological determinant of student persistence in automated environments [15], [17]. Taken together, these findings strengthen global evidence that psychological confidence helps mitigate technology-related apprehension and encourages active engagement in complex learning systems.

5.2 Partial mediation through AIA

The observed partial mediation effect of AIA suggests that two processes operate simultaneously. The first is cognitive-behavioral: students with higher OLSE tend to use structured digital strategies such as effective time management, gradual task progression, and strategic engagement with online systems—behaviors that reduce the risk of cognitive overload even under anxiety. The second is affective-emotional: stronger efficacy beliefs lower apprehension toward AI, freeing emotional resources that support focus and performance. This dual-pathway explanation is consistent with previous studies demonstrating that self-efficacy moderates the adverse emotional impact of anxiety on learning outcomes [6], [20], [26]. Earlier models suggested that anxiety might fully mediate the influence of self-efficacy, yet the persistence of a direct path to DWB in the present study indicates that self-efficacy contributes to emotional regulation in ways that extend beyond anxiety reduction.

5.3 Why these effects are stronger in engineering education

Engineering programs represent some of the most digitally demanding disciplines in higher education. Students frequently work with coding environments, simulation software, and algorithm-based evaluation systems. Constant interaction

with such automated platforms can generate stress, fatigue, and cognitive strain. Unlike general humanities programs, engineering students in Jordan are required to master high-stakes AI-mediated tools, such as automated code debuggers and algorithmic optimization software. The perceived 'black-box' nature of these tools, where the logic behind a machine-generated error is not always transparent, intensifies AI anxiety. In this environment, self-efficacy serves as a stabilizing psychological resource, enabling students to interpret technical errors constructively, recover more quickly from setbacks, and differentiate valuable feedback from irrelevant system noise. Self-efficacy, therefore, acts as a psychological stabilizer, allowing students to navigate these technical ambiguities without experiencing a decline in their DWB. These interpretations echo earlier findings that engineering self-efficacy supports persistence and satisfaction despite demanding workloads [25], [27].

5.4 Contextual significance in Jordan

The inclusion of both public and private Jordanian universities—each differing in policy maturity, infrastructure, and technological readiness—highlighted the importance of personal psychological resources such as self-efficacy. In institutional environments where support systems are inconsistent, self-efficacy functions as a transferable asset that enables adaptability and emotional balance. This observation aligns with regional findings showing that limited institutional readiness often heightens technology-related anxiety among Jordanian university students [21], [22].

Cultural expectations add another layer of pressure. The strong societal emphasis on academic and engineering excellence amplifies performance demands, making self-efficacy even more valuable as a source of control and predictability. These dynamics parallel findings from other Arab universities. Cross-cultural findings involving Arab university students indicate that higher AI-related self-efficacy and competency are associated with more positive attitudes toward AI and better well-being outcomes [30]. Thus, this study extends international theories of self-efficacy and DWB to a Middle Eastern context, illustrating how individual agency can compensate for structural and institutional limitations. This interpretation is consistent with prior evidence from Jordan during the COVID-19 transition, where OLSE was positively associated with online learning satisfaction, whereas anxiety-related factors were negatively associated with satisfaction outcomes among university students [35], [36]. The convergence across pandemic-driven distance learning and AI-mediated learning environments supports self-efficacy as a stable protective resource in technologically intensive higher education.

5.5 Methodological credibility

To ensure methodological rigor, the study followed the recommended two-step approach for SEM [33]. In the first step, a pooled measurement model was evaluated using CFA to verify the psychometric adequacy of the latent constructs—OLSE, AIA, and DWB—prior to testing the structural relationships. The CFA results indicated satisfactory measurement quality. All standardized factor loadings were statistically significant and exceeded recommended thresholds. CR values ranged from 0.91 to 0.95, and AVE values ranged from 0.78 to 0.86, providing strong evidence of convergent validity. Given the high correlations observed between some constructs, discriminant validity was explicitly assessed using the Fornell–Larcker criterion, which

confirmed that each construct remained empirically distinct. To address potential common-method bias, Harman's single-factor test was conducted and indicated that no single factor accounted for the majority of variance. The convergence between the SEM results and the supplementary multiple regression analysis further supports the robustness and stability of the findings, consistent with prior methodological evidence [25]. Differences in effect magnitudes between OLS regression and SEM are methodologically expected because OLS uses observed composite scores (retaining measurement error), whereas SEM estimates relationships among latent variables while accounting for unreliability.

5.6 Pedagogical implications

Given that self-efficacy emerged as a key factor, educators should prioritize building students' confidence and digital literacy early in their academic journey. This implication aligns with evidence from an online technical writing and communication skills course showing that students' self-efficacy and perceived competencies can remain high in fully online delivery, alongside strong learning outcome attainment [37]. Introducing AI tools through low-stakes practice, establishing transparent assessment standards, and incorporating reflective learning opportunities can reduce uncertainty and foster comfort with technology [13], [20]. Furthermore, embedding digital self-regulation micro-skills—including attention control, workload pacing, goal calibration, and digital minimalism—into introductory courses can translate confidence into consistent digital wellness habits [26], [27], and [29]. These strategies echo global initiatives led by the OECD and the European Commission, which emphasize the importance of complementing technical expertise with DWB and psychological literacy [18], [19].

5.7 Limitations

Despite its methodological rigor, several limitations should be acknowledged. First, the study employed a cross-sectional design, which restricts the ability to establish causal relationships among OLSE, AIA, and DWB. Although the hypothesized directional paths were grounded in social cognitive theory and supported by structural modeling, longitudinal or experimental designs are required to confirm temporal ordering and causality. Second, all constructs were measured using self-report instruments collected at a single time point. While multiple procedural and statistical remedies were applied—including Harman's single-factor test and a latent method factor sensitivity analysis—to mitigate common-method bias, the possibility of shared method variance cannot be entirely eliminated. Third, the sample was drawn exclusively from engineering undergraduates in Jordan. Although this context is theoretically relevant due to the high digital and AI intensity of engineering programs, caution is warranted when generalizing the findings to other disciplines, educational systems, or cultural settings. Finally, the strong correlations observed among the latent constructs likely reflect their close conceptual relationships within technology-intensive learning environments. While discriminant validity was supported through CFA and the Fornell-Larcker criterion, future research may benefit from incorporating additional constructs—such as AI literacy, perceived algorithmic transparency, or fairness—to further disentangle overlapping psychological dimensions.

5.8 Future directions

Future research should employ longitudinal or experimental designs to establish the causal sequence among OLSE, AIA, and DWB. Including additional variables—such as AI literacy, perceptions of algorithmic transparency, and fairness—could improve the explanatory power of the model. Comparative studies across STEM and non-STEM disciplines may reveal whether these psychological processes are specific to engineering or more broadly applicable to AI-supported education [28], [29], [31]. A mixed-methods approach that integrates quantitative modeling with qualitative interviews would also provide a more nuanced understanding of how students experience algorithmic learning environments and how these experiences influence their digital well-being.

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