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AI Literacy and Genz's Intentions to Reduce Digital Habits: A Moderated Mediation Analysis Approach for Mindful Technology Usage, Digital Self-Efficacy, and Peer Influence through PLS-SEM, ANN, and fsQCA

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Abstract

Purpose – There is a close association between the fast acceptance of artificial intelligence (AI) tools in higher education and the rise in the time spent on screens by Generation Z students on a daily basis. Previous studies have focused on AI literacy as a facilitator of AI adoption and utilization. This paper attempts to find out whether AI literacy, self-regulation, digital wellbeing literacy, academic productivity, and FoMO predict students' willingness to reduce digital habits through mindful technology use, moderated by digital self-efficacy and peer influence.

Design/methodology/approach –Data were obtained through survey from 556 Generation Z college students and analysed using PLS-SEM. The measurement model was examined in terms of reliability and validity, the structural model was tested for direct, mediation and moderation effect, while the predictive relevance was estimated via a blindfolding approach. The results were validated using ANN analysis and fsQCA.

Findings –All five antecedents were found to be significant predictors of mindful technology usage in the hypothesized direction, and mindful technology use was a significant predictor of digital wellness and hence acted as a partial mediator of the five relationships. AI literacy was uniquely significant as a predictor of digital wellness. Digital self-efficacy selectively moderated only AI literacy and self-regulation paths, whereas peer influence did not moderate the relationship between mindful technology usage and digital wellness. The results from ANN highlighted the non-linear significance of digital well-being awareness and AI literacy, while fsQCA identified three equifinal combinations that could predict high digital wellness.

Practical implications – Educational Institutions should combine their AI-literacy training with digital wellbeing programmes instead of conducting them independently, focus on instilling self-efficacy and self-regulation over peer norm messages, and treat AI-literacy training as a wellbeing intervention in addition to an academic skills intervention.

Originality/value – This paper shifts the focus of AI literacy from its association with digital usage to digital disengagement and presents a methodologically triangulated (PLS-SEM, ANN, fsQCA) explanation for how competency, awareness, and affect influence the Generation Z intention to engage less with harmful digital practices.

Keywords: AI literacy; digital wellness; mindful technology use; digital self-efficacy; peer influence; self-regulation; fear of missing out; PLS-SEM; artificial neural network (ANN); fsQCA

Introduction

Within a relatively short period of time, generative AI has evolved from something that people do not understand into something they recognize within college institutions. Multinational survey data reveal that more than nine out of ten students within higher education institutions currently make use of generative AI with more than half making use of generative AI tools such as ChatGPT on a weekly basis (Freeman, 2025). Research conducted on over 23,000 students in 109 countries reveals that ChatGPT has been used widely by students to generate ideas as well as summarize academic information (Ravšelj et al., 2025). With the rapid development of AI, AI literacy has become an important skill for all.

This change occurs amid a trend in students' interaction with digital technologies in which the members of Generation Z – those born between the middle of the 1990s and the early 2010s – indicate the most frequent use of screens daily compared to other generations. According to the survey findings, members of Generation Z use their screens for nearly nine hours daily (Kumar, 2026). On the other hand, the vast majority of members of this generation intentionally try to decrease their daily time with screens for the purpose of protecting their wellbeing. While such a contradiction between two opposite needs of students is common in the digital wellbeing research, it acquires additional theoretical meaning after the introduction of AI features into existing competing digital devices and applications.

This dual nature informs the current study. Two streams of literature have been cultivated largely separately. The information systems and human computer interaction literature considers AI literacy as primarily predictive of AI adoption, continuance, and performance, accounting for why individuals engage with technology but not why or how they may engage less (Wang et al., 2023). Meanwhile, the health psychology and digital wellbeing stream emphasizes the importance of self-regulation, mindfulness, and awareness as precursors to lower problematic usage of technologies; however, this line of work largely does not incorporate AI literacy because it has predated the widespread rise of generative AI (K. W. Brown & Ryan, 2003; Przybylski et al., 2013). A gap in theory thus arises because it is unknown whether an ability that promotes increased AI usage can also promote decreased digital technology usage.

The second research gap builds on the first. Research on digital habits reduction usually employs the straightforward model of effect or mediation and does not consider the moderating circumstances in which an ability, like AI literacy, leads to reduced technology use. Two of the most likely moderators to be considered are self-efficacy and social context; however, there have been few attempts to estimate their simultaneous effects via the variance-based SEM model suitable for prediction-based exploratory research (Hair et al., 2019).

Thirdly, there is a gap related to the research population. Generation Z students are the biggest users of platforms using algorithms and the generation of people who grew up amid the freely available AI, but relatively few researchers have focused on these people. Moreover, the gap has practical implications as many universities value AI-literacy abilities but do not provide courses in these competencies despite students' growing need in them (Freeman, 2025). Educational Institutions also conduct digital wellbeing programs to reduce excessive use of

smartphones and social media, However, rarely do such programs interact with AI literacy education despite the similarity in the self-regulatory bases of the two concepts. Recognizing the relationship between these concepts and under what circumstances will help educational institutions come up with coordinated services for students.

This study attempts to fill these gaps through the development and empirical examination of an integrated framework where AI literacy, self-regulation, digital well-being awareness, academic productivity, and fear of missing out affect digital wellness through mindful technology usage, which refers to the conscious rather than habitual use of digital technology. The two moderating variables in the model include digital self-efficacy, which will enhance the relationship between antecedents and mindful technology usage, and peer influence, which will reduce the relationship between mindful technology usage and digital wellness because of students' high susceptibility to peer influences. This study is driven by three research questions:

RQ1: Are AI literacy, self-regulation, digital well-being knowledge, academic productivity, and fear of missing out direct and indirect determinants of the intention to reduce digital habits through mindful technology use?

RQ2: Is digital self-efficacy a moderator of the impact of these antecedents on mindful technology use?

RQ3: Is peer influence a moderator of the relationship between mindful technology use and the intention to reduce digital habits?

The rest of the paper provides a review of the theory and existing literature, along with the formulation of the study's hypotheses, the description of the research methodology, the results of measurement and structural models analysis, and the ANN and fsQCA analysis, and concludes with the discussion, implications, and conclusion.

Theoretical background

The current study has been based on the tenets of two different theories that complement each other. The Social Cognitive Theory (SCT) (Bandura, 1986) postulates that behaviour is a function of the interrelation of personal, behavioral, and environmental components, with self-efficacy being an important element of the theory (the belief of a person in their ability to execute the task). According to SCT, people rely more heavily on their knowledge and self-regulation capabilities when they have high levels of self-efficacy. The same approach may be applied to the first component of the proposed model where AI literacy, self-regulation, digital well-being awareness, and academic productivity can be seen as personal competence or self-knowledge that SCT suggests will influence behavior when the level of digital self-efficacy is high and not influence it when the level of self-efficacy is low. Digital self-efficacy is therefore modelled as a moderator of the effect of these antecedents on mindful technology use.

The Theory of Planned Behavior (TPB) (Ajzen, 1991) expands on this idea with an explanation of how cognitions and emotions are transformed into behavioral intention, the immediate predictor of behavior, through attitude, subjective norm, and perceived behavioral

control. Since the measure of digital wellness used in this study is measured as behavioral intention (Ajzen, 2006; McMahon & Aiken, 2015), TPB justifies the incorporation of mindful-technology-use-to-intention path, and also justifies the introduction of peer influence, which is theoretically connected to TPB's subjective norm, as the moderator of that path, since the peers' attitudes and behaviors could intensify or mitigate a person's intention to make changes. SCT and TPB together demonstrate how personal competencies are turned into mindful technology use with digital self-efficacy in place, and how mindful technology use transforms into a strong intention to break away from the digital practices, in line with the contemporary conceptualizations of technology misuse as multi-factorial (Brand et al., 2016).

The concept of AI literacy is defined as an ability to use AI systems in a proper manner (Ng et al., 2021; B. Wang et al., 2023). It has become much broader and now not only covers knowledge about the mechanisms underlying functioning of AI systems but also the ability to evaluate the information generated by AI systems and to use them responsibly (Pinski & Benlian, 2024). However, the existing body of research is mainly concerned with how AI literacy influences technology usage, i.e., adoption, performance, and learning (Pinski & Benlian, 2024). The measures used in different studies are not always consistent, and there is even some evidence of overestimation of AI literacy by poorer performers (Ng et al., 2021), suggesting AI literacy can also function as a coping mechanism.

Related research studies correlate AI literacy with anxiety, self-efficacy, attitude, responsible, and irresponsible usage of AI (Canbeldek Erol et al., 2026), with personal innovativeness in the context of generative-AI adoption (Wu et al., 2025), with technology readiness (Flavián et al., 2022), and with student engagement and mental wellbeing (Y. Wang & Wang, 2024). Within the scope of SCT framework, the current research hypothesizes that AI literacy serves as a critical thinking and self-regulating ability: people who possess information about the design and functioning of AI-based technologies are more likely to realize the process of their automatic usage and thus contribute to the development of their own intention for achieving digital wellness.

H1: AI literacy positively and significantly affects mindful technology use.

H7: AI literacy has a positive direct effect on digital wellness

Self-regulation, which is defined as the ability to monitor, evaluate, and regulate one's own behavior in order to align it with their goals (J. M. Brown et al., 1999; Carey et al., 2004), has gained importance in digital-technology research owing to the prevalence of automatic smartphone use. While the causality in the relationship between self-regulation and technology use is contested in existing studies and impossible to resolve using the cross-sectional design of the current study, past evidence has found a positive relationship between self-regulation and mindful technology use, given that the latter requires self-regulation, since mindfulness itself depends on the capacity to delay automatic responses and notice deviations from one's plans (K. W. Brown & Ryan, 2003).

H2: Self-regulation has a significant positive effect on mindful technology use.

Digital well-being awareness refers to an individual's awareness of the influence of digital-technology usage on his or her emotional and general well-being, including the awareness of possible symptoms of overuse (Türk Kurtça, 2026). It is still not clear whether this kind of awareness leads to changes in behavior without being transformed into mindful technology usage. This research suggests that digital well-being awareness stimulates mindful technology use that in its turn facilitates the formation of the intention to change bad habits. This assumption is supported by the fact that there are various approaches to forming healthy technology-related habits among people (Uslu, 2025), that digital well-being predicts low internet addiction likelihood regardless of age (Singha & Singha, 2025), that the developed Digital Well-Being Scale positively correlates with FOMO and digital identity (Gómez Yepes et al., 2025), and that university students' dependence on AI technologies negatively correlates with their well-being (Jenifer & Seethalakshmy, 2025).

H3: There is a significant positive effect of digital well-being awareness on mindful technology use.

Academic productivity refers to students' perceived accomplishment of academic activities without the use of digital distractions, which are assessed through a reverse-scored procrastination scale (Tuckman, 1991). Procrastination and digital distraction are closely related in the existing research; however, there is some controversy about the direction of their relationship. This research accepts the theory that students who feel academically productive and not distracted are more likely to use technology mindfully, in accordance with the literature on how AI virtual assistants help with independent and productive learning (Ignacio, 2026) and influence academic productivity (Bates, 2023).

H4: Academic productivity has a significant positive effect on mindful technology use.

The fear of missing out (FoMO) which involves anxiety about being constantly connected in order not to miss out on any rewarding experience (Przybylski et al., 2013) is one of the most well-documented antecedents of smartphone and social media addiction which includes smartphone dependence, increased frequency of use and reduced offline satisfaction (Elhai et al., 2017), and more recently the engagement in viral trends by young adults (Wardah & Harlianty, 2026); researchers have even proposed an opposite construct of "joy of missing out" (Safaria, 2026). Since FoMO is associated with the anxiety and the urge to connect that oppose mindful technology use, it should be the only negative antecedent of the latter, a pattern that would also support the discriminant validity of the mediator.

H5: Fear of missing out significantly negatively affects mindful technology use.

Mindful technology use (MTU) refers to conscious rather than habitual technology use; it is adopted in this research from the Mindful Attention Awareness Scale (K. W. Brown & Ryan, 2003) based on existing evidence of associations between mindfulness and smartphone use distractions (Throuvala et al., 2020). Mindfulness has been considered a vital factor in educational technology and digital workplace environment (Henriksen et al., 2022; Jarrahi et al., 2023); experienced users seem to combine mindfulness and technology usage into a habitual process without separating them (Li et al., 2024); screen time tracking applications are related to

higher levels of mindfulness (Oeldorf-Hirsch & Chen, 2022); digital detox programs enhance well-being of students (Balasubramanian, 2024); and IT mindfulness and AI literacy have been identified as predictors of lifelong learning through engagement and autonomy (Lim & Teh, 2026). On the other hand, the relationship between MTU and intention to reduce the use of technology, the proximal predictor of behavioral change according to TPB, remains unclear. This research claims that mindful use raises awareness of the costliness and patterns of one's own digital behavior and, therefore, increases the intention to limit non-productive use irrespective of the source of mindful state.

H6: Mindful technology use has a significant positive effect on digital wellness.

Based on the SCT-TPB integration outlined earlier, mindful technology use is proposed as the mediating variable through which the relationship between the aforementioned antecedents and digital wellness occurs, because distal capabilities and emotional states are considered too distal to have an impact on behavioral intentions, and therefore have to function through the more proximal state of mindful technology use. Given the fact that some of the antecedents are positively valent and one negatively valent, the mediating role of mindful technology use for each antecedent will be tested separately using the bootstrapped specific indirect effects.

H8a–H8e: Mindful technology use mediates the relationship between AI literacy, self-regulation, digital well-being awareness, academic productivity, and fear of missing out, and digital wellness.

Digital self-efficacy (DSE), defined by (Ulfert-Blank & Schmidt, 2022) as "confidence in using digital tools for searching, assessing, communicating, working, and troubleshooting," operationalizes the self-efficacy concept in SCT, and it is assumed that this variable would determine whether awareness and competence would lead to behavioural change or not because intention–behaviour gaps, and not change, result from awareness or competence but lack of confidence. As the antecedents vary in terms of how direct the measures of personal agency (both AI literacy and self-regulation are examples of agentic competencies whereas digital well-being awareness, academic productivity, and FoMO are more evaluative or affective in nature), DSE might not play the same moderator's role in each of the five paths, although SCT predicts a positive amplification of their impact, tested here for all five of them simultaneously.

H9: Digital self-efficacy positively moderates the relationship between the five antecedents and mindful technology use, such that these relationships are stronger when digital self-efficacy is high.

Peer influence (PI), adopted from the Resistance to Peer Influence scale but measured as vulnerability rather than resistance (Steinberg & Monahan, 2007), reflects how much technology usage behaviour is determined by peer pressure; peer effects are well-researched factors that are established as predictors of social media usage of adolescents and emerging adults. In the current research, however, PI is considered to be a moderator of the mindful-technology-use-to-intention relationship, because a student who understands his/her overuse of

technology might not have the strength to oppose peers' expectations of being constantly available. This factor plays the role in TPB that the subjective norm variable does.

H10: Peer influence moderates the relationship between mindful technology use and digital wellness.

Table 1 gives an overview of nine constructs utilized in the current study along with sources where measurement items for these constructs were adopted.

Table 1. Constructs and Sources of Measurement Items

Construct	Source of measurement items
AI Literacy	(Ma & Chen, 2024)
Self-Regulation	(Pichardo et al., 2014)
Digital Well-being Awareness	(Türk Kurtça, 2026)
Academic Productivity	(Alattas et al., 2026)
Fear of Missing Out	(Przybylski et al., 2013)
Mindful Technology Use	(Sandra, 2025)
Digital Self-Efficacy	(Ulfert-Blank & Schmidt, 2022)
Peer Influence	(Chatterjee et al., 2021)
Digital Wellness	(McMahon & Aiken, 2015)

Source(s): Authors owns work, adapted from the cited studies.

Conceptual Framework

Figure 1 combines the above ten hypotheses into one conceptual framework. Five antecedents namely, AI literacy, self-regulation, digital well-being awareness, academic productivity, and fear of missing out, are presented as the parallel determinants of mindful technology utilization, which, in turn, determine digital well-being, and the former also directly impacts the latter. Digital self-efficacy acts as the first stage moderator of the five antecedent-mediator relationships, while peer influence is the second stage moderator of the mediator-outcome relationship, thus forming the first and second stage moderated mediation design (Hayes, 2017).

H1: AI literacy has a significant positive impact on mindful technology usage. **H2:** Self-regulation has a significant positive impact on mindful technology usage. **H3:** Digital well-being consciousness has a significant positive impact on mindful technology usage. **H4:** Academic productivity has a significant positive impact on mindful technology usage. **H5:** Fear of missing out has a significant negative impact on mindful technology usage. **H6:** Mindful technology usage has a significant positive impact on digital wellness. **H7:** AI literacy has a significant positive direct impact on digital wellness. **H8a-e:** Mindful technology usage is a mediator of the relationships between AI literacy, self-regulation, digital well-being consciousness, academic productivity, and fear of missing out, and digital wellness, respectively. **H9:** Digital self-efficacy positively moderates the relationships between the five antecedents and mindful technology usage. **H10:** Peer influence moderates the relationship between mindful technology usage and digital wellness.

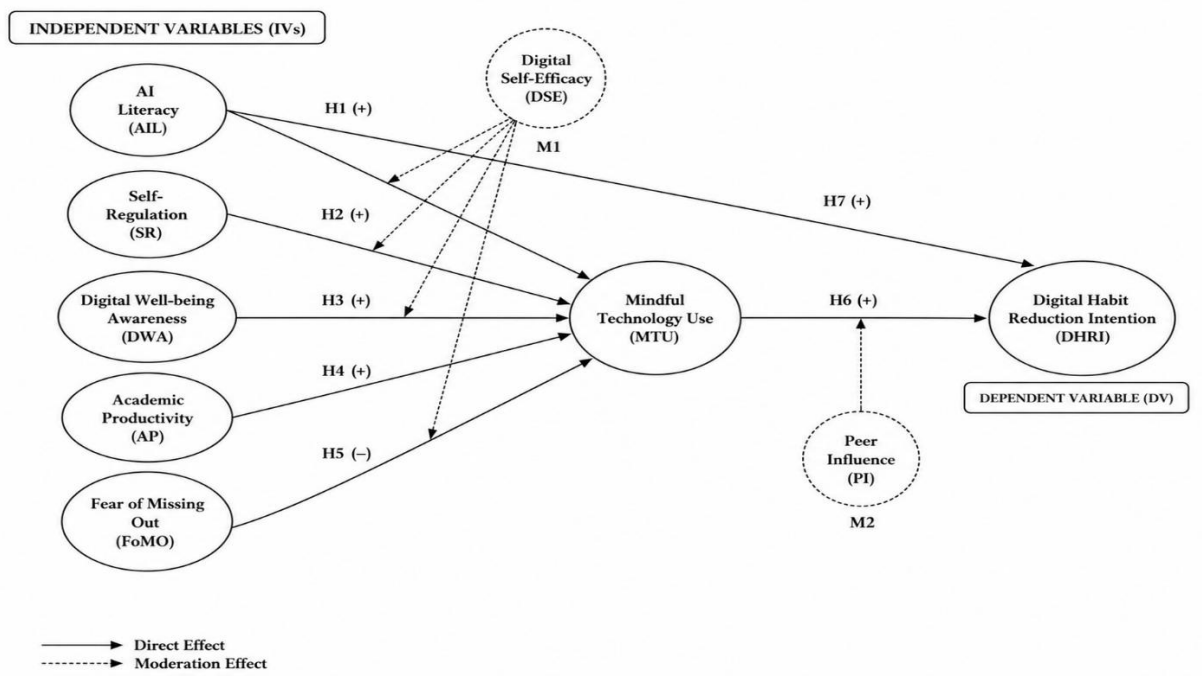


Figure 1. Proposed research model of AI literacy, self-regulation, digital well-being awareness, academic productivity, and fear of missing out on digital wellness, mediated by mindful technology use and moderated by digital self-efficacy and peer influence.

Research methodology

Positivism serves as the philosophical foundation of this investigation due to the intention to verify specific hypotheses about the connections among AI literacy, self-regulation, digital well-being awareness, academic productivity, fear of missing out, mindful technology use and digital well-being. The deductive, cross-sectional survey approach was employed, which allows for conducting hypothesis tests in a moderated-mediation context but precludes any causal conclusion about the directionality of the hypothesized relationships.

The quantitative, correlational research approach was conducted via a self-administrated questionnaire that measures nine variables on the seven-point Likert scale (1 = strongly disagree, 7 = strongly agree), along with questions regarding gender, age category, institution, educational level, field of study, average daily screen time, average daily social media time, and type of artificial intelligence tool usage and its duration. Such an approach enables the investigation of direct, mediated, and moderated relationships between the variables in one structural model, which is not possible in case of using simple regression or ANOVA due to the presence of ten hypotheses.

This study considered graduate and postgraduate Generation Z students of Biju Patnaik University of Technology, Rourkela, Odisha, India as our target population. Non-probability purposive sampling method was applied to this study due to the lack of a complete sampling frame of participants, which is the standard practice in the application of the PLS-SEM technique to criteria-defined rather than list-defined population (Hair et al., 2019). The number of 556

valid cases remained after applying the data screening process, more than the sample size suggested for models of such structure under the ten-times rule, in which the needed sample size depends on the greatest number of formative indicators or structural path that are directed to one construct (Hair et al., 2019; Kock & Hadaya, 2018).

A 47-item questionnaire was constructed by contextual adaptation of previously validated scales and ensured the empirical grounding of the measurement model in the context of digital-technology and digital-wellbeing. AI literacy was operationalized using six items (AIL1-AIL6) from (Ma & Chen, 2024); self-regulation with six items (SR1-SR6) from (Pichardo et al., 2014); and digital wellbeing awareness using five items (DWA1-DWA5) from (Türk Kurtça, 2026). Academic productivity was measured with the help of five reverse-scored items (AP1–AP5) according to (Alattas et al., 2026), since the original measure is associated with procrastination; FoMO was assessed with the help of five items (FOMO1–FOMO5) according to (Przybylski et al., 2013). Mindful technology usage was considered a mediator variable in the current study and was measured with the help of six items (MTU1–MTU6) according to (Sandra, 2025); digital self-efficacy was used as a first-stage moderator variable and was assessed with five items (DSE1–DSE5) according to (Ulfert-Blank & Schmidt, 2022); and peer influence was used as a second-stage moderator variable and was measured with the help of five reverse-scored items (PI1–PI5) according to (Chatterjee et al., 2021), since the original measure reflects resistance to peer influence. The final construct, digital wellness, was measured with the help of six items (DW1–DW6) based on (McMahon & Aiken, 2015). All items were reworded for context while preserving the substance of the original measures, with reverse scoring applied wherever necessary to maintain consistent score orientation.

Data analysis used Partial Least Squares Structural Equation Modelling (PLS-SEM) conducted in SmartPLS 3.2.9, a variance-based approach appropriate for this study's predictive objectives as well as the application of a model that uses reflective constructs, mediation, and moderation (Hair et al., 2019). Internal consistency (Cronbach's Alpha, Rho_A, Composite Reliability), convergent validity (AVE and outer loadings), and discriminant validity (Fornell–Larcker criterion and Heterotrait–Monotrait ratio) were assessed in the measurement model, with collinearity among indicators measured through Variance Inflation Factor. The structural model was tested through bootstrapping with 5,000 subsamples with Bias-Corrected Accelerated Confidence Intervals used to compute standard errors, t-values, and p-values of path coefficients (Hair et al., 2019). Explained variance was measured using R^2 and Adjusted R^2 on mindful technology use and digital wellness, while effect size of predictors was measured using f^2. Predictive relevance was determined through blindfolding using an omission distance of 7 to calculate Q^2 values, while model fit was measured by Standardized Root Mean Square Residual (SRMR) of both saturated and estimated models. The mediation hypotheses (H8a–H8e) were tested via bootstrapped specific indirect effects, considered supported when $t > 1.96$ ($p < .05$), in accordance with current mediation testing procedures (Nitzl et al., 2016). Hypotheses about moderation (H9 and H10) were tested using the product-indicator method, with interaction terms

constructed in SmartPLS and assessed through bootstrapping; significant interactions were examined using simple slope analysis ±1 standard deviation of the moderator.

In order to address the linear and compensatory nature of the PLS-SEM framework, an artificial neural network (ANN) analysis was carried out using the PLS-SEM-ANN two-stage approach (Leong et al., 2013). The estimation was done for a multilayer perceptron feed forward back propagation model with sigmoid activation function for ten trained models, using a 90/10 training/testing split, under ten-fold cross-validation procedure; predictive performance was measured through root mean square error (RMSE), and sensitivity analysis produced normalised predictor importance scores, allowing for a non-linear robustness test of the PLS-SEM predictor orderings (Qi et al., 2026; Sharma et al., 2024).

Lastly, fuzzy-set qualitative comparative analysis (fsQCA) examined the conditions that formed sufficient configurations for digital well-being, adding to the net-effects symmetry approach used by PLS-SEM, and fitting for conjunctural, equifinality, and asymmetric relations (Ragin, 2009; Woodside, 2013). The construct scores were transformed into fuzzy-set membership values ranging from 0 to 1, based on full membership, crossover, and non-membership criteria, and then truth table analysis was performed using 0.75 as the solution consistency requirement with an appropriate frequency threshold (Pappas & Woodside, 2021). Intermediate solutions were evaluated in terms of consistency, raw coverage, and unique coverage.

Findings

Measurement model assessment

In accordance with the traditional practice of two-stage PLS-SEM modeling, the measurement (outer) model was evaluated prior to the estimation of the structural model. Reflective indicators were found to have loads greater than 0.70 on their respective constructs (0.723–0.919). As shown in in Table 2, Cronbach's alpha varied between 0.872 and 0.927, rho_A from 0.875 to 0.947, and composite reliability from 0.903 to 0.944, which is well above the critical value of 0.70 required to ensure internal consistency reliability (Hair et al., 2019); the average variance extracted varied from 0.610 to 0.773, exceeding the 0.50 threshold for convergent validity in every case.

Table 2. Reliability and Convergent Validity

Construct	Cronbach's α	rho_A	*Composite* Reliability (CR)	AVE
AI Literacy	0.894	0.900	0.919	0.655
Digital Wellness	0.887	0.892	0.914	0.641
Digital Self-Efficacy	0.927	0.947	0.944	0.773
Digital Well-being Awareness	0.880	0.909	0.912	0.675
Fear of Missing Out	0.895	0.923	0.922	0.704
Mindful Technology Use	0.872	0.875	0.903	0.610
Peer Influence	0.890	0.925	0.916	0.685
Academic Productivity	0.905	0.932	0.929	0.723
Self-Regulation	0.913	0.920	0.933	0.698

Note. All values exceed conventional thresholds (α, rho_A, CR ≥ 0.70; AVE ≥ 0.50), confirming internal consistency reliability and convergent validity.

The measure of discriminant validity has been obtained using Fornell-Larcker Criterion and Heterotrait-Monotrait Ratio (HTMT). As shown in Table 3 that the square root of each construct's AVE (Diagonal) value is higher than their correlation with any other construct which fulfills the Fornell-Larcker Criterion. The HTMT ratio in Table 4 is between 0.044 to 0.447 for all the constructs, which is much lower than both conservative (0.85) and liberal (0.90) cut off values (Henseler et al., 2015).

Table 3. Discriminant Validity — Fornell-Larcker Criterion

Construct	AIL	SR	DWA	AP	FoMO	MTU	DW	DSE	PI
AI Literacy (AIL)	0.810								
Self-Regulation (SR)	0.058	0.836							
Digital Well-being Awareness (DWA)	0.092	-0.027	0.822						
Academic Productivity (AP)	-0.048	0.039	0.055	0.850					
Fear of Missing Out (FoMO)	-0.013	-0.011	0.042	-0.040	0.839				
Mindful Technology Use (MTU)	0.249	0.406	0.171	0.208	-0.262	0.781			
Digital Wellness (DW)	0.301	0.186	0.123	0.048	-0.042	0.389	0.801		
Digital Self-Efficacy (DSE)	0.013	-0.038	0.095	-0.065	-0.064	-0.170	-0.016	0.879	
Peer Influence (PI)	0.069	-0.014	-0.061	0.059	0.053	0.013	0.029	0.097	0.828

Table 4. Discriminant Validity — Heterotrait-Monotrait Ratio (HTMT)

Construct	AIL	SR	DWA	AP	FoMO	MTU	DW	DSE	PI
AI Literacy (AIL)	—								
Self-Regulation (SR)	0.074	—							
Digital Well-being Awareness (DWA)	0.108	0.062	—						
Academic Productivity (AP)	0.088	0.061	0.078	—					
Fear of Missing Out (FoMO)	0.050	0.054	0.072	0.059	—				
Mindful Technology Use (MTU)	0.276	0.447	0.188	0.229	0.284	—			
Digital Wellness (DW)	0.336	0.199	0.134	0.083	0.092	0.437	—		
Digital Self-Efficacy (DSE)	0.076	0.061	0.119	0.076	0.070	0.180	0.067	—	
Peer Influence (PI)	0.090	0.044	0.085	0.078	0.096	0.066	0.049	0.113	—

Note. All HTMT values fall well below the 0.85/0.90 cut-offs, supporting discriminant validity.

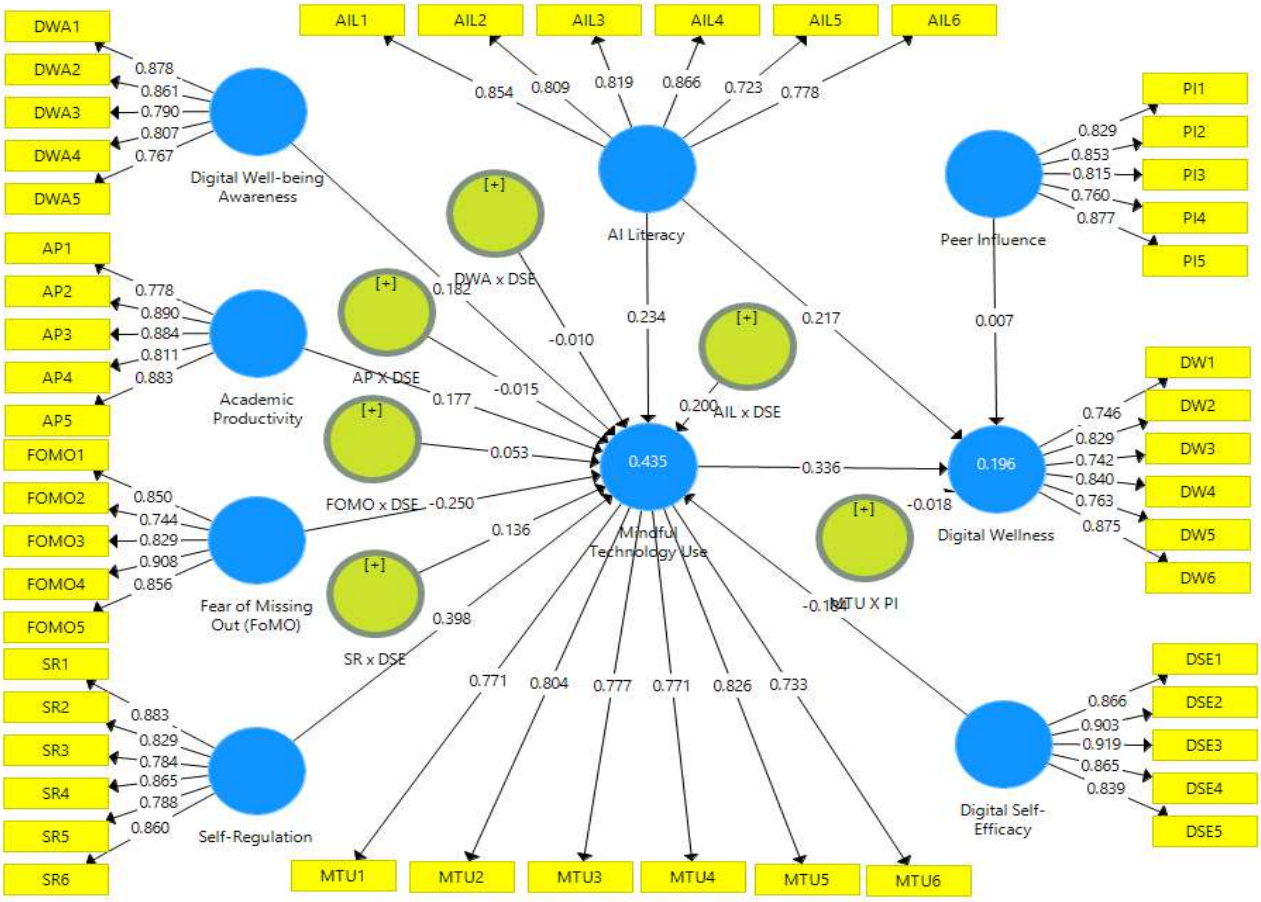


Figure 2. Estimated structural model with standardised outer loadings, path coefficients, and R^2 values for the endogenous constructs (mindful technology use, digital wellness), produced by the PLS algorithm in SmartPLS.

On the indicator level, collinearity was at an acceptable level, where variance inflation factors varied from 1.64 (indicators of mindful technology use) to 3.72 (indicators of digital self-efficacy), all lower than the conservative threshold of 5 (Hair et al., 2019). In sum, these findings demonstrate reliability, convergent validity, discriminant validity, and acceptable collinearity, which provide the estimation of the structural model shown in Figure 2, including standardised outer loadings, R^2 values, and path coefficients.

Structural model assessment

The ability of these models to explain variance in the endogenous variables was evaluated using R^2 and adjusted R^2 measures for both models, as well as f^2 effect sizes for all predictors (Table 5). The variable of mindful technology use yielded $R^2 = 0.435$ (adjusted $R^2 = 0.424$), which shows that the five predictors along with their interaction with digital self-efficacy were able to account for roughly 43.5% of the variance in this construct – a moderate amount of

explanatory power as per (Cohen, 1988) guidelines. In the case of digital wellness, $R^2 = 0.196$ (adjusted $R^2 = 0.190$) was yielded, which is a low-to-moderate amount of explanatory power that is not surprising given the nature of digital wellness being dependent upon two direct predictors (mindful technology use and AI literacy) plus a non-significant peer-influence interaction, leaving considerable residual variance attributable to factors outside the present model, such as habit strength, device dependency, or platform design.

Table 5. Coefficient of Determination (R^2) and Effect Sizes (f^2)

Predictor	**Outcome**	**f^2**	**Effect Size**
Self-Regulation	Mindful Technology Use	0.276	Medium-to-large
Fear of Missing Out	Mindful Technology Use	0.106	Small-to-medium
AI Literacy × Digital Self-Efficacy	Mindful Technology Use	0.065	Small
Digital Self-Efficacy	Mindful Technology Use	0.058	Small
Digital Well-being Awareness	Mindful Technology Use	0.056	Small
Academic Productivity	Mindful Technology Use	0.054	Small
AI Literacy	Mindful Technology Use	0.094	Small
Self-Regulation × Digital Self-Efficacy	Mindful Technology Use	0.032	Small
Fear of Missing Out × Digital Self-Efficacy	Mindful Technology Use	0.005	Negligible
Digital Well-being Awareness × Digital Self-Efficacy	Mindful Technology Use	0.000	Negligible
Academic Productivity × Digital Self-Efficacy	Mindful Technology Use	0.000	Negligible
Mindful Technology Use	Digital Wellness	0.131	Small-to-medium
AI Literacy	Digital Wellness	0.055	Small
Peer Influence	Digital Wellness	0.000	Negligible
Mindful Technology Use × Peer Influence	Digital Wellness	0.000	Negligible

Note. f^2 thresholds follow Cohen (1988): ≥0.02 small, ≥0.15 medium, ≥0.35 large. R^2 (endogenous constructs): mindful technology use = 0.435 (adj. = 0.424); digital wellness = 0.196 (adj. = 0.190).

The predictive relevance (tested using blindfolding procedure – omission distance = 7) showed Q^2 values of 0.258 for mindful technology use and 0.122 for digital wellness, both exceeding zero, with the former falling into the medium to large category and the latter into the small to medium category according to the common criteria of interpreting Q^2 values (small = 0.02, medium = 0.15, large = 0.35). Model fit measured using SRMR was 0.049 for the estimated model and 0.048 for the saturated model, which were lower than 0.08, representing acceptable fit (Henseler et al., 2016). Normed fit index (NFI) value was 0.818; however, since NFI is known to underestimate the fit compared to covariance-based SEM and is not considered adequate as an indicator of fit on its own, SRMR will be used as a main fit criterion here.

Hypothesis testing: direct effects

Structural paths were estimated through bootstrapping with 5,000 subsamples. Table 6 reports the path coefficients, t-values, and p-values for the seven direct effects; all seven hypotheses were supported.

Table 6. Structural Path Coefficients — Direct Effects (H1–H7)

Hyp.	Path	β	t-value	p-value	Decision
H1	AI Literacy → Mindful Technology Use	0.234	6.740	<0.001	Supported
H2	Self-Regulation → Mindful Technology Use	0.398	13.980	<0.001	Supported
H3	Digital Well-being Awareness → Mindful Technology Use	0.182	5.713	<0.001	Supported
H4	Academic Productivity → Mindful Technology Use	0.177	5.719	<0.001	Supported
H5	Fear of Missing Out → Mindful Technology Use	-0.250	7.460	<0.001	Supported
H6	Mindful Technology Use → Digital Wellness	0.336	9.084	<0.001	Supported
H7	AI Literacy → Digital Wellness	0.217	5.682	<0.001	Supported

Note. Two-tailed testing; bootstrapping = 5,000 subsamples, bias-corrected and accelerated. β = standardized path coefficient.

Mindfulness was the leading antecedent of mindful technology use (β = 0.398), followed by AI literacy (β = 0.234), FOMO (β = –0.250, the only negative antecedent in the model as expected), digital wellness awareness (β = 0.182), and academic productivity (β = 0.177). Out of the two factors predicting digital wellness, the former (β = 0.336) outweighed the latter, the direct effect of AI literacy (β = 0.217), which is in line with the proposed model.

Mediation analysis

The indirect effects (with 5,000 resamples) for each mediation hypothesis were calculated. As Table 7 shows, all five indirect effects were statistically significant, proving H8a–H8e.

Table 7. Specific Indirect Effects (Mediation via Mindful Technology Use)

Hyp.	Indirect Path	β	t-value	p-value	Decision
H8a	AI Literacy → MTU → DW	0.078	5.583	<0.001	Supported
H8b	Self-Regulation → MTU → DW	0.134	6.959	<0.001	Supported
H8c	Digital Well-being Awareness → MTU → DW	0.061	4.654	<0.001	Supported
H8d	Academic Productivity → MTU → DW	0.059	5.092	<0.001	Supported
H8e	Fear of Missing Out → MTU → DW	-0.084	5.803	<0.001	Supported

Note. MTU = mindful technology use; DW = digital wellness.

Because AI literacy showed both a significant direct effect (H7) and a significant indirect effect (H8a) on digital wellness, and both effects share the same positive direction, mindful

technology use is best characterised as a complementary partial mediator of the AI literacy–digital wellness relationship. For self-regulation, digital well-being awareness, academic productivity, and fear of missing out- none of which was specified with a direct path to digital wellness — the effect on digital wellness operates only indirectly through mindful technology use, an indirect-only mediation pattern.

Moderation analysis

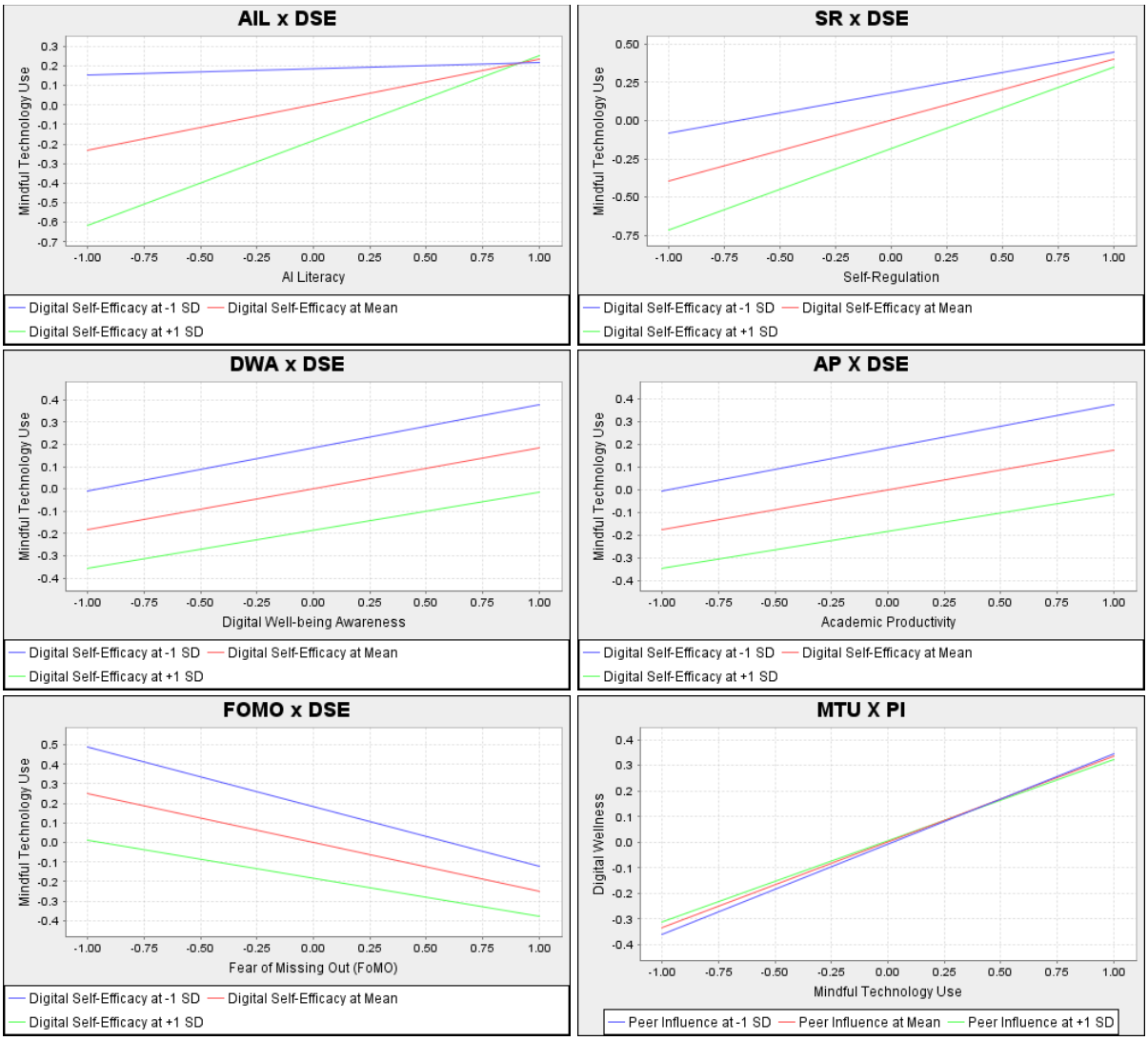
The interaction effects were examined using the product indicator approach (Table 8): five interaction variables for Hypothesis H9 (moderating effect of digital self-efficacy on the antecedent-mindful-technology-use relationship) and one for Hypothesis H10 (peer influence moderating the mindful-technology-use–digital-wellness path).

Table 8. Moderation Results — Interaction Effects (H9–H10)

Hyp.	Interaction Term → Outcome	β	t-value	p-value	Decision
H9 (i)	AI Literacy × DSE → Mindful Technology Use	0.200	5.864	<0.001	Significant
H9 (ii)	Self-Regulation × DSE → Mindful Technology Use	0.136	4.026	<0.001	Significant
H9 (iii)	Digital Well-being Awareness × DSE → Mindful Technology Use	-0.010	0.302	0.763	Not significant
H9 (iv)	Academic Productivity × DSE → Mindful Technology Use	-0.015	0.470	0.638	Not significant
H9 (v)	Fear of Missing Out × DSE → Mindful Technology Use	0.053	1.575	0.116	Not significant
H10	Mindful Technology Use × Peer Influence → DW	-0.018	0.352	0.725	Not significant

Note. DSE = digital self-efficacy; DW = digital wellness.

H9 received partial support since digital self-efficacy significantly amplified the impact of AI literacy and self-regulation on mindful technology use, but did not significantly moderate the effect of digital wellness awareness, academic productivity, or FOMO paths - indicating that self-efficacy's amplifying role, though uniformly predicted by SCT, is in practice confined to the two inherently agentic antecedents. H10 was unsupported in that peer influence did not significantly moderate the relationship between mindful technology use and digital wellness, implying that once mindful technology use had been cultivated, peer influence does not have any significant influence on the intentions to limit one's digital behavior. Simple slope graphs are shown in Figures 3-8.



Figures 3–8. Simple-slope plots for the six tested interaction effects: AI Literacy × Digital Self-Efficacy, Self-Regulation × Digital Self-Efficacy, Digital Well-being Awareness × Digital Self-Efficacy, Academic Productivity × Digital Self-Efficacy, and Fear of Missing Out × Digital Self-Efficacy (all on mindful technology use), and Mindful Technology Use × Peer Influence (on digital wellness).

Table 9. Overall Summary of Hypothesis Testing Results

Hypothesis	Relationship	Decision
H1	AI Literacy → Mindful Technology Use	Supported
H2	Self-Regulation → Mindful Technology Use	Supported
H3	Digital Well-being Awareness → Mindful Technology Use	Supported
H4	Academic Productivity → Mindful Technology Use	Supported
H5	Fear of Missing Out → Mindful Technology Use	Supported (negative)
H6	Mindful Technology Use → Digital Wellness	Supported
H7	AI Literacy → Digital Wellness (direct)	Supported

H8a–e	Mindful technology use mediates all five antecedent–DW relationships	Supported
H9	Digital Self-Efficacy moderates antecedent–MTU relationships	Partially supported (2 of 5)
H10	Peer Influence moderates MTU–DW relationship	Not supported

Complementary analysis: artificial neural network

A non-linear robustness test to complement the results of the structural path analysis above and in line with the two-stage PLS-SEM-ANN procedure (Leong et al., 2013) involved the estimation of ten MLP ANNs using ten-fold cross validation. The network architecture used is shown in Figure 9, while Figure 10 displays the RMSEs and importance of predictors from the ten estimations.

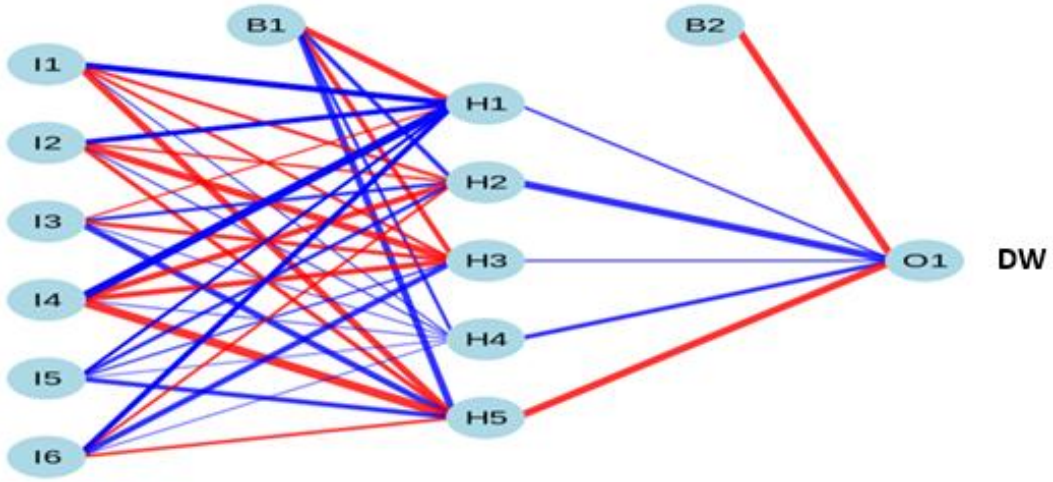


Figure 9. Estimated ANN model architecture, showing input-layer constructs (I1–I6), bias units (B1–B2), hidden-layer neurons (H1–H5), and the output neuron (O1, digital wellness).

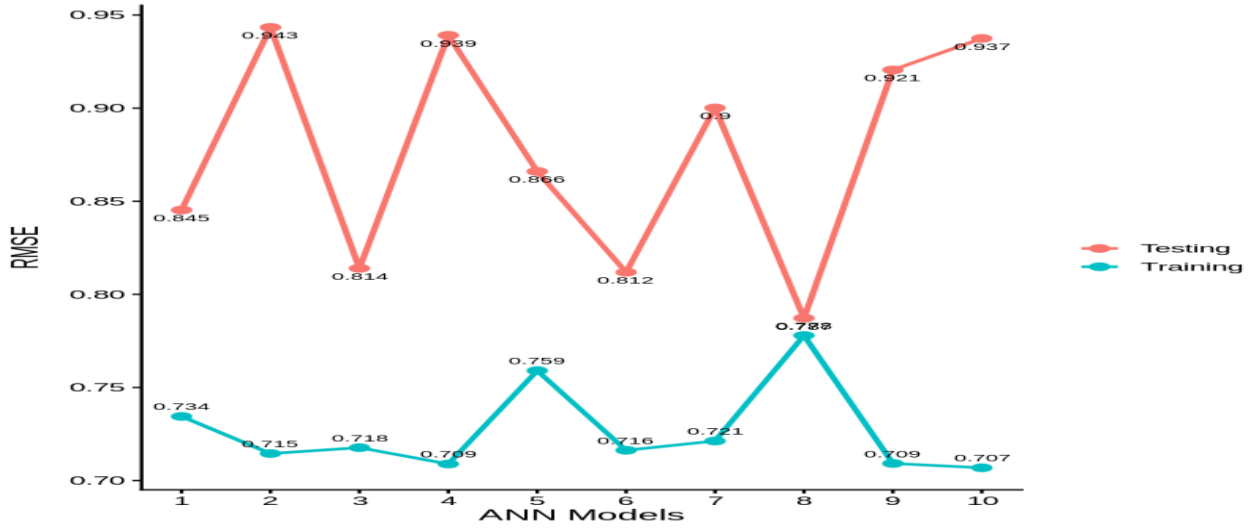


Figure 10. Root mean square error (RMSE) values for the training and testing samples across the ten ANN models.

Table 10. Artificial Neural Network (ANN) Model Results: Relative and Normalized Importance

ANN Model	AI Literacy	Digital Self-Efficacy	Digital Well-being Awareness	Fear of Missing Out	Mindful Technology Use
ANN1	0.19	0.59	1.00	0.73	0.52
ANN2	0.56	0.35	1.00	0.36	0.37
ANN3	0.62	0.50	1.00	0.13	0.96
ANN4	0.79	0.33	0.23	0.19	1.00
ANN5	1.00	0.35	0.85	0.26	0.73
ANN6	1.00	0.45	0.55	0.40	0.56
ANN7	0.50	0.61	1.00	0.56	0.22
ANN8	0.43	0.39	1.00	0.47	0.57
ANN9	0.46	0.10	0.42	1.00	0.43
ANN10	1.00	0.09	0.21	0.89	0.19
Mean	0.66	0.38	0.73	0.50	0.56
Normalized Importance	90%	52%	100%	69%	77%

The normalised importance scores in Table 10 show digital well-being awareness as having the highest non-linear predictive importance (100%), followed by AI literacy (90%), mindful technology use (77%), fear of missing out (69%), and digital self-efficacy (52%). The above order is quite similar to that observed from the PLS-SEM path coefficients but places more weight on digital well-being awareness and AI literacy compared to the linear version of these coefficients, in line with the overall observation that the ANN sensitivity analysis technique is capable of identifying non-compensatory effects not captured using the compensatory, additive SEM approach (Leong et al., 2013). RMSE values across the ten models were small and consistent between the training and testing partitions.

Complementary analysis: fuzzy-set qualitative comparative analysis

Since both PLS-SEM and ANN models compute symmetric net effect associations, fsQCA was further applied to find out configurations of AI literacy, digital self-efficacy, digital wellness knowledge, fear of missing out, and mindful technology usage that lead to high digital wellness, as per the equifinality approach to causality (Ragin, 2008). Table 11 presents the findings along with consistency and coverage scores.

Table 11. fsQCA Configurations for High Digital Wellness

Condition / Metric	Solution 1	Solution 2	Solution 3
AI Literacy	●	⊗	
Digital Self-Efficacy	●	●	⊗
Digital Well-being Awareness		●	●
Fear of Missing Out	⊗		●
Mindful Technology Use	●	⊗	
Consistency	0.8875	0.8238	0.9280
Raw Coverage	0.4519	0.3405	0.7503
Unique Coverage	0.1001	0.0103	0.2380

The first solution demonstrates that being AI literate, digitally self-efficient, and mindful technology use as well as having no fear of FOMO is sufficient for high digital wellness (consistency = 0.89, raw coverage = 0.45). This confirms the results of PLS-SEM analysis that AI literacy and mindfulness in using technology are crucial factors, now combined with self-efficacy and no FoMO. The second solution demonstrates that digital self-efficiency and awareness of digital well-being are jointly sufficient regardless of being AI literate and mindful in using technology (consistency = 0.82, raw coverage = 0.34). Here, there is an alternative awareness-based approach to achieving digital well-being, which could not be revealed through a single dominant pathway of PLS-SEM. The third solution, the most powerful empirically (consistency = 0.93, coverage = 0.75), involves digital well-being awareness and FoMO in the absence of digital self-efficiency: thus, students who are highly aware of their digital well-being and at the same time fearful of missing out, while not self-efficient in their digital activities, can still form reduction intentions, which is impossible to reveal through net-effect linear model due to negative FoMO PLS-SEM average effect. Together, the three solutions demonstrate equifinality: no single antecedent is sufficient alone, and different combinations of conditions can each independently produce high digital wellness.

Discussion

This study evaluated the potential impact of AI literacy along with self-regulation, digital well-being awareness, academic productivity, and FoMO on digital wellness through mindful technology use, while taking into account digital self-efficacy and peer influence as moderating factors. The findings provide strong support to the theoretical framework; however, the moderation effect seems to be more selective than expected in this study.

The positive association between AI literacy and both mindful technology use (H1) and digital well-being (H7) builds on prior research where AI literacy has been considered a key predictor of confident and efficient adoption of AI (Pinski & Benlian, 2024; Y. Wang & Wang, 2024). These findings demonstrate that AI literacy is a bi-faceted concept: the same evaluative and reasoning skills that help in AI adoption can also help in reduction-related technology use. It is an interesting metacognitive perspective on AI literacy discussed in (Pinski & Benlian, 2024) applied to the behavioral aspects of AI adoption that have been mostly overlooked in prior studies.

Self-regulation was found to be the strongest predictor of mindful technology use (β = 0.398), supported by a plethora of literature demonstrating that the capacity to control one's impulses and monitor their goals is an essential element for behaviour change (Carey et al., 2004). Moreover, the discriminant value of the model was strengthened by fear of missing out, which was the only maladaptive antecedent and negative predictor of mindful technology use (H5), as demonstrated by the strong association between FoMO and problem use (Elhai et al., 2017). Lending indirect support to the mediator's construct validity, since the outcome responded to competence and awareness factors and to FoMO in the theoretically predicted, opposite directions.

The moderation results bring into question the simple application of the Social Cognitive Theory perspective here. Only the paths between two of the antecedents and mindful technology use were affected by digital self-efficacy – the relationship between AI literacy and mindful technology use as well as the link between self-regulation and mindful technology use were moderated. One possible reason is that AI literacy and self-regulation are agency constructs, where the belief in one's ability with technology can be a natural moderator. Digital well-being awareness and academic productivity, in turn, are more reflective and FoMO is an affective construct; hence, the beliefs about one's self-efficacy may simply not affect them. Thus, the pattern of selective moderation enhances the perspective of Social Cognitive Theory.

Finally, there was an unexpected result where the significant negative main effect of digital self-efficacy on mindful technology use was observed ($\beta = -0.184$). The result is in line with the explanation of overconfidence based on the self-efficacy literature: those individuals who feel very competent in using technology do not have to check their performance because they trust themselves.

Also, peer influence did not influence the relationship between mindful use of technology and digital well-being (H10 not supported). There is quite a large amount of adolescent and emerging adult literature indicating the importance of peer influence on digital activity; one possible explanation may be that even though peer influence is likely to affect how adolescents start engaging in digital activities, and how they continue them, creating an intention to reduce their activity is an individual action that is less susceptible to peer influence, irrespective of its actual realization.

In this respect, the supplementary ANN analysis adds additional insights to our understanding: while self-regulation was the most influential linear predictor of mindful technology use under PLS-SEM framework, the ANN sensitivity analysis showed that digital well-being awareness and AI literacy were the most important non-linear predictors. This does not indicate an inconsistency because in PLS-SEM–ANN models there is often a difference between the linear path coefficients and non-linear predictive importance of a certain construct due to non-compensatory or threshold effects (Leong et al., 2013). Practically, it suggests digital well-being awareness may matter more than its relatively modest standardised coefficient implies.

Further insight comes from the fsQCA findings. Instead of having one dominating path to wellness, there are three empirically meaningful paths, which means that digital wellness is equifinal and can come about via the agentic path (AI literacy, digital self-efficacy, and mindful technology use, with low levels of FoMO), the awareness-driven path (digital self-efficacy and digital well-being awareness, irrespective of AI literacy and mindful use), or the path combining awareness and anxiety (digital well-being awareness and FoMO, irrespective of digital self-efficacy). In this case, we are talking about the path that would not be revealed using a symmetric and additive model. The latter path, in particular, is very important since FoMO, being a consistent negative PLS-SEM predictor of mindful technology use, can coexist with digital wellness when digital well-being awareness is high enough.

Implication of the study

This research makes the following theoretical contributions. First, it helps to re-conceptualize AI literacy as an interesting construct that can explain disengagement-oriented, self-regulatory behavior as well as the adoption-oriented one since existing AI literacy models (Ng et al., 2021; Pinski & Benlian, 2024) have mostly been validated with regards to adoption behavior while this research proves that the same literacy competence predicts the intention of reducing technology use. Second, the paper proposes a coherent SCT-TPB theory of digital habit-reduction by specifying both the antecedents of interest and the process of how exactly they affect the outcome, i.e., by providing the mediation model that involves mindful technology use and by identifying some conditions that need to be met for the antecedents to affect the outcome (digital self-efficacy and peer influence). Specifically, the conditional moderating role of self-efficacy (significant for agentic antecedents, non-significant for evaluative/affective antecedents) suggests that self-efficacy's behavioral effect might depend on whether the antecedent is agentic or evaluative.

Thirdly, the research is able to elucidate the role of mediation in the field under investigation, in that it clearly distinguishes the complementary partial mediation of AI literacy from the pure indirect mediation of the other four antecedent constructs, thus uncovering the unique ability of the former to mediate digital well-being through a pathway distinct from that of mindless consumption of technology. Lastly, through the use of the three methods of analysis (PLS-SEM, ANN, and fsQCA) in a moderated mediation analysis study, more prevalent in research on technology adoption than on technology reduction, it becomes evident that constructs which are significant in linear prediction through PLS-SEM are significant in nonlinear prediction as well.

The results have several practical implications for a variety of stakeholders. For universities' administration and student support programs, in light of the fact that AI literacy positively affects digital wellness both directly and indirectly through mindful use of technology, integrating modules related to self-regulation and mindful use into the current or upcoming AI literacy program may be more efficient in improving students' wellbeing than each program in isolation. For managers of students' wellbeing or counseling programs, in view of the fact that peer influence does not moderate the link between mindfulness and intention to reduce use, programs based on peer norm messaging are not likely to effectively facilitate the effect of mindful awareness on reduction intention; rather, resources should be devoted to the development of AI literacy and self-regulation, along with digital self-efficacy interventions, considering the potential for high self-efficacy to undermine mindful use.

Platform developers would find the association between AI literacy and reduction meaningful as it implies that design elements which increase user knowledge about AI-powered recommendation or engagement engines could reasonably help users pursue their own self-regulation goals, something worth joint work by platform designers and researchers in digital wellbeing.

Policymakers working on higher education and digital-literacy standards may find the results helpful in understanding that AI literacy should be seen as both an academic skills intervention and a wellbeing one, thus, justifying its placement in funding areas related to students' mental health and digital wellbeing programs rather than technological education only. And finally, for intervention designers, the research provides a validated moderated mediation model – antecedents of competencies and affective states channeled into mindful technology use via self-efficacy rather than social norms – which can be applied to other reduction domains of digital behavior, such as social media, gaming, and companion AI usage.

Conclusion

The present study explored the extent to which AI literacy, combined with self-regulation, digital well-being awareness, academic productivity, and fear of missing out, influences the intention to decrease digital engagement among university students of Generation Z through the mediator of mindful technology use, contingent on the moderating effects of digital self-efficacy and peer influence. The analysis conducted using PLS-SEM based on survey responses of 556 students showed that all five predictors had a significant impact on mindful technology use as hypothesized; that mindful technology use had a significant impact on digital wellness and fully or partially mediated the five predictor relationships; that AI literacy had a unique direct impact on digital wellness; that digital self-efficacy selectively moderated the impact of the two most proactive predictors; and that peer influence did not moderate the relationship between mindful technology use and the intention to decrease digital engagement. These results were validated by an ANN model, which demonstrated the non-linear predictive value of the key model constructs, as well as by an fsQCA, which revealed that there were multiple ways for achieving high levels of digital wellness by varying combinations of the same key constructs. In totality, the research reframes AI literacy from merely being an adoption-focused skill into one that holds behavioural importance in relation to digital well-being, and also gives an empirical explanation on how competence, consciousness, and affect influence the intent to discontinue maladaptive digital practices in an AI-laden academic context. Given that generation Z increasingly employs the use of generative AI in studying, communicating, and seeking information, developing the self-regulatory skills necessary to enable this age group to use these tools effectively and not obsessively will become increasingly relevant.

There are certain limitations that need to be considered regarding the interpretation of these findings and areas for further research to be explored. Due to the cross-sectional nature of the study, it is impossible to draw any causal relations between the variables, which means that while the proposed order of relationships (for example, self-regulation being a predictor and not a result of using technology in a mindful way) is theoretically plausible, it is not empirically supported and should be tested using other designs, such as longitudinal or panel research, and whether digital wellness leads to lower use of devices (e.g., lower passive screen time). Common method variance is a likely issue because all the constructs were measured by self-reports at one point of time; however, VIF values were acceptable.

Outcome, which measures behavioral intentions, rather than change in behavior, is appropriate in view of the known intention-behavior gap acknowledged by TPB. The significant negative effect of digital self-efficacy, despite its moderating effect in two paths, calls for direct qualitative or experimental studies of why this might be so. It is not clear whether the findings can be generalized to populations from Generation Z in different settings as the generalizability of the sample is uncertain, especially in view of the known cross-cultural variation in adopting AI as well as peer influence. Since the model shows a relatively low explanatory power concerning digital well-being ($R^2 = 0.196$), there is still some significant amount of variance that is not explained by such constructs as strength of habit, limitations at the device-level, or personality traits that have not been considered here, and future research could investigate differences between kinds of digital habits (social media, generative-AI companion, or gaming) since the antecedents and mechanisms that were identified here can vary depending on a specific habit type. Finally, despite the fact that the ANN and fsQCA analyses are good sources of robustness check, the ANN part used only ten networks that were trained without any comparison to other kinds of architecture or algorithmic solutions, and the fsQCA calibration included researcher judgment concerning membership thresholds; hence, these approaches should be seen as complementary, but not fully independent, robustness check to PLS-SEM results, and future research can test ANN approach using different machine learning solutions and perform fsQCA separately for different subgroups, for example, according to field of study or baseline screen-time level.

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