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Self-Determined Learning, Digital Competence, and Learning Styles as Predictors of Students' Attitudes toward Flipped Learning

Muhammad Haristo Rahman[1*], Amiruddin[2], Nurlaela[3]
[1,2,3] *Universitas Negeri Makassar, Indonesia*

Corresponding e-mail : m.haristo.rahman@unm.ac.id

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ABSTRACT

Flipped learning effectiveness depends heavily on student attitudinal acceptance, yet prior research has typically examined its determinants in isolation focusing separately on technology acceptance, self-regulation, or learning preferences. This study proposes and tests an integrated structural model linking Self-Determined Learning (SDL), Digital Competence (DC), and Learning Style (LS) to students' attitudes toward flipped learning (SFLIPP) among undergraduates in Indonesian higher education. A cross-sectional survey was administered to 395 students, and data were analyzed using Partial Least Squares Structural Equation Modeling (PLS SEM). The measurement model demonstrated robust reliability and validity (AVE > .50; CR > .838; HTMT < .90). Results showed that Learning Style was the strongest direct predictor of attitudes (β = .413, p < .001), followed by Digital Competence (β = .190, p < .001) and Self-Determined Learning (β = .164, p < .001). SDL exerted a substantial total effect on SFLIPP (β = .535), with approximately 69.3% of this effect mediated indirectly predominantly through LS (71.4% of the mediated portion) rather than DC (28.6%). The model explained 42.7% of the variance in attitudes. These findings indicate that fostering positive attitudes toward flipped learning requires a holistic approach that simultaneously strengthens student agency, cultivates responsible digital competence, and ensures pedagogical preference alignment.

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INTRODUCTION

The rapid digitization of higher education has catalyzed a paradigm shift in instructional design, moving beyond traditional lecture based models toward more flexible, learner centered approaches. Among these innovations, flipped learning has emerged as a prominent pedagogical strategy that inverts the conventional learning sequence by relocating information delivery to the pre-class phase typically through video lectures or structured readings while reserving face to face sessions for active engagement, collaborative problem solving, and higher order cognitive application (Ayuningsih et al., 2025; O'Flaherty & Phillips, 2015). Meta analytic and scoping reviews consistently affirm that this model yields positive educational outcomes, particularly when pre class materials are carefully curated and in class activities are deliberately orchestrated to promote deep learning (Strelan et al., 2020; Kapur et al., 2022). However, the sustainability and effectiveness of flipped learning are not determined by structural design alone; students' attitudinal disposition toward this non traditional format remains a critical mediating variable that influences participation, engagement, and long term adoption.

Theoretical frameworks from multiple disciplinary perspectives offer complementary explanations for why and how flipped learning succeeds. From a motivational standpoint, Self-Determination Theory (SDT) posits that autonomy, competence, and relatedness are fundamental psychological needs that foster intrinsic motivation (Ryan & Deci, 2000), while cognitive load theory suggests that flipped environments can optimize mental effort by separating knowledge acquisition from complex application, provided that students possess adequate self regulatory capacities (Abeysekera & Dawson, 2015). Concurrently, technology acceptance research rooted in the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT) underscores the pivotal roles of perceived usefulness, ease of use, and social influence in shaping behavioral intentions toward technology mediated learning (Venkatesh & Davis, 2000; Alyoussef, 2022). Empirical evidence further demonstrates that self regulated learning support embedded in pre class materials significantly enhances learning outcomes, highlighting student agency as an indispensable element within the flipped learning ecosystem (van Alten et al., 2020).

Despite this burgeoning body of evidence, existing literature exhibits a notable fragmentation in examining the determinants of students' attitudes toward flipped learning. Prior studies have predominantly adopted a siloed analytical approach: some investigate technology acceptance factors in isolation, others focus exclusively on independent learning strategies, and still others examine learning style preferences without accounting for their interplay with technological and self-regulatory dimensions. Consequently, an integrated structural understanding of how Self-Determined Learning, digital competence, and learning styles *collectively* shape attitudinal outcomes remains conspicuously underdeveloped. This theoretical compartmentalization limits our ability to discern the relative contributions and potential mediation mechanisms among these interrelated constructs, thereby obscuring a holistic picture of the antecedents to flipped learning acceptance.

To address this lacuna, the present study proposes an integrative structural model that simultaneously examines three defining dimensions. First, Self-Determined Learning (SDL) is conceptualized through the lenses of self determination theory and heutagogy, encompassing agency, active participation, reflective planning, and self evaluation (Ryan & Deci, 2000; Blaschke, 2012). Second, Digital Competence (DC) refers to the operational proficiency in utilizing digital tools including Learning Management Systems (LMS), video conferencing platforms, and AI assisted applications for academic purposes, aligned with the European Digital Competence Framework (Ilomäki et al., 2016; Vuorikari et al., 2016; Fan & Wang, 2022). Third, Learning Style (LS) captures students' pedagogical preferences (e.g., collaborative versus individual; autonomous versus guided), commonly assessed through the Felder Silverman Index of Learning Styles (ILS) model, which has direct implications for comfort and compatibility with flipped instructional methods (Felder & Spurlin, 2005).

This study aims to analyze and empirically test the influence of SDL, DC, and LS on students' attitudes toward flipped learning (hereinafter abbreviated as SFLIPP) through three hypothesized pathways: (1) the indirect effect of SDL via DC on SFLIPP, (2) the indirect effect of SDL via LS on SFLIPP, and (3) the direct effect of SDL on SFLIPP. The conceptual contribution of this research lies in its synthesis of motivational, technological, and pedagogical preference variables within a unified structural equation framework an integration rarely attempted in previous flipped learning research. Practically, the findings are expected to furnish actionable guidance for educators seeking to design differentiated interventions that strengthen students' self directed learning capabilities, cultivate responsible digital literacy (including AI literacy), and align instructional activities with diverse learning preferences, ultimately fostering more favorable attitudes toward flipped learning implementation.

METHOD

Research Design and Approach

This study employed a quantitative, explanatory research design with a cross-sectional survey approach to examine the structural relationships among latent variables. Specifically, a Partial Least Squares Structural Equation Modeling (PLS-SEM) approach was utilized to test both the measurement properties of the constructs and the hypothesized structural pathways simultaneously. PLS-SEM was selected over covariance based SEM (CB SEM) for several reasons: first, it is particularly robust when distributional assumptions of normality are violated; second, it is well-suited for predictive research models involving multiple latent constructs and mediating variables; and third, it allows for the simultaneous assessment of reflective measurement models and the estimation of direct and indirect effects within a single analytical framework (Hair et al., 2022; Sarstedt & Cheah, 2019). Given the present study's objective to predict students' attitudes toward flipped learning through both direct and mediated pathways, PLS-SEM provided the most appropriate methodological foundation.

Population and Sampling

The target population consisted of actively enrolled undergraduate students across various faculties at Indonesian higher education institutions who had experienced flipped learning instruction defined here as courses utilizing pre-class digital materials (video lectures or structured readings) followed by face-to-face sessions dedicated to application, collaboration, and problem-solving. The sampling frame was restricted to students from the class of 2022 to ensure a comparable level of academic maturity and exposure to technology mediated instruction.

Participants were recruited using simple random sampling techniques. A total of 395 respondents met the inclusion criteria: (1) active enrollment status during the data collection period, and (2) completion of at least one course implementing a flipped learning model with pre-class online materials. The final sample size of 395 exceeded the minimum threshold required for PLS-SEM analysis. Following the 10-times rule which stipulates that the minimum sample size should be ten times the maximum number of structural paths directed at a particular endogenous construct (Hair et al., 2022) this sample was deemed more than adequate for reliable path parameter estimation and construct reliability assessment.

Demographically, the sample was predominantly female (n = 251; 63.54%) compared to male (n = 144; 36.46%). Faculty distribution revealed that the majority of participants were enrolled in the Faculty of Engineering (n = 226; 57.22%), followed by the Faculty of Education (n = 118; 29.87%). Smaller representations came from the Faculty of Economics (n = 22; 5.57%), Faculty of Agriculture (n = 9; 2.28%), Faculty of Mathematics and Natural Sciences (n = 8; 2.03%), Faculty of Social and Cultural Sciences (n = 7; 1.77%), and Faculty of Health (n = 5; 1.27%). Table 1 presents the complete demographic profile.

Table 1. Demographic Profile

Demographic Profile	Count	Proportion
Gender		
Male	144	36.46%
Female	251	63.54%
Faculty		
Faculty of Engineering	226	57.22%
Faculty of Education	118	29.87%
Faculty of Economics	22	5.57%
Faculty of Mathematics and Natural Sciences	8	2.03%
Faculty of Social and Cultural Sciences	7	1.77%

Faculty of Health	5	1.27%
Faculty of Agriculture	9	2.28%

Instruments and Measurements

The research instrument was developed through an extensive literature review and subsequently adapted to the Indonesian higher education context. The questionnaire consisted of 16 reflective indicators measuring four latent constructs. All items were operationalized as reflective indicators, whereby the latent construct is assumed to cause the measured variables (Hair et al., 2022).

Self-Determined Learning (SDL) was measured using five reflective indicators capturing: (1) clarity of learning objectives, (2) active participation in learning activities, (3) reflection and planning behaviors, (4) self-evaluation of understanding, and (5) self-initiated efforts to improve technology related skills. These indicators align with the theoretical dimensions of agency, autonomy, and self-regulation derived from Self Determination Theory and heutagogical principles (Ryan & Deci, 2000; Blaschke, 2012).

Digital Competence (DC) was operationalized through five indicators assessing digital habits for academic purposes: (1) submitting assignments via email, (2) accessing course materials through a Learning Management System (LMS), (3) participating in video conferencing sessions (e.g., Zoom or Google Meet), (4) utilizing Artificial Intelligence tools (e.g., ChatGPT) for completing academic tasks, and (5) using AI tools for searching learning materials. These indicators correspond to the operational skills dimension within the European Digital Competence Framework (Ilomäki et al., 2016; Vuorikari et al., 2016).

Learning Style (LS) was assessed using three preference indicators: (1) preference for group work versus individual study, (2) campus attendance preferences, and (3) initiative in solving problems independently before seeking guidance. While the full Felder-Silverman ILS model encompasses four dimensions (Active/Reflective, Sensing/Intuitive, Visual/Verbal, Sequential/ Global), the present study operationalized LS through these three behavioral preference indicators to align with the specific structural demands of flipped learning, which emphasizes pre-class autonomy and in-class collaboration (Felder & Spurlin, 2005; Karabulut-Ilgu et al., 2018).

Attitudes toward Flipped Learning (SFLIPP) was measured through three indicators: (1) perceived improvement in conceptual understanding, (2) perceived usefulness of the flipped approach, and (3) behavioral intention to continue participating in flipped learning courses in the future.

All items were measured on a 10 point Likert type scale ranging from 1 (*strongly disagree*) to 10 (*strongly agree*). The item phrasing was carefully adjusted to reflect the specific behavioral and attitudinal content of each construct, ensuring face validity and contextual appropriateness for Indonesian university students.

Data Collection Procedure

Data collection was conducted during the active academic semester using an online questionnaire distributed through institutional email and Learning Management System portals. Prior to administration, a brief explanation of the study's objectives, voluntary participation, and confidentiality assurances was provided. This study received ethical clearance from the institutional review board, and all participants provided informed consent. Participation was entirely voluntary and anonymous. Respondents were required to confirm their experience with flipped learning courses before proceeding to the substantive items. The questionnaire included attention-check items to ensure response quality. Data collection spanned a four-week period, with reminder notifications sent at weekly intervals to maximize response rates and minimize non-response bias.

Data Analysis Techniques

Data analysis was performed using SmartPLS 4.0 software and followed the standard two-stage analytical procedure for PLS-SEM. Stage 1: Measurement Model Assessment (Outer Model). The psychometric properties of the instrument were evaluated through several established criteria. Indicator reliability was assessed via outer loadings, with values above 0.70 considered satisfactory; indicators with loadings between 0.40 and 0.70 were retained only if their removal would compromise content validity. Convergent validity was established through the Average Variance Extracted (AVE), where values exceeding 0.50 indicate that the construct explains more than half of the variance of its indicators (Fornell & Larcker, 1981). Internal consistency reliability was examined using Composite Reliability (CR) and Cronbach's Alpha (α), with thresholds of > 0.70 indicating acceptable reliability. Discriminant validity was verified using the Heterotrait-Monotrait Ratio of Correlations (HTMT), employing the conservative criterion of HTMT < 0.85 with the upper bound of the 95% confidence interval below 1.00 (Henseler et al., 2015).

Stage 2: Structural Model Assessment (Inner Model). The structural relationships were evaluated through several metrics. The coefficient of determination (R^2) was examined for each endogenous construct to assess the model's explanatory power. Path coefficients (β) were estimated to determine the strength and direction of direct relationships, while indirect effects were computed as the product of path coefficients along the mediating pathways (e.g., SDL → LS → SFLIPP; SDL → DC → SFLIPP). The significance of all path coefficients was tested using bootstrapping with 5,000 resamples to generate standard errors and p-values. The total effect of SDL on SFLIPP was calculated as the sum of its direct effect and indirect effects via the two mediators. Additionally, the relative magnitude of mediation was assessed by comparing the specific indirect effects against the total effect.

RESULTS AND DISCUSSION

Results

Measurement Model Assessment

The adequacy of the measurement model was evaluated by examining indicator reliability, internal consistency, convergent validity, and discriminant validity. Indicator reliability was assessed through outer loadings. All indicators demonstrated satisfactory loadings ranging from 0.697 to 0.955. Specifically, the Self-Determined Learning (SDL) construct exhibited strong loadings between 0.807 and 0.875. The Digital Competence (DC) indicators ranged from 0.697 to 0.803, with two indicators (DC1 and DC3) marginally approaching the 0.70 threshold; these were retained due to their substantive theoretical relevance and contribution to content validity. The Learning Style (LS) indicators ranged from 0.714 to 0.844, while the Attitudes toward Flipped Learning (SFLIPP) indicators demonstrated very high loadings from 0.915 to 0.955, indicating that these items reliably reflect their respective constructs.

Table 2. Reliability and Validity of the scale used (SEM) Model

Variable	Cronbach's α	Composite Reliability	AVE
Self-Determined Learning (SDL)	0.901	0.927	0.717
Digital Competence	0.782	0.849	0.531
Learning Style	0.709	0.838	0.634
Attitudes towards Flipped Learning	0.928	0.954	0.874

Convergent validity was confirmed as the Average Variance Extracted (AVE) for all constructs exceeded the conservative threshold of 0.50: SDL (AVE = 0.717), DC (AVE = 0.531), LS (AVE = 0.634), and SFLIPP (AVE = 0.874). Internal consistency reliability was established through Composite Reliability (CR) and Cronbach's Alpha (α). The CR values ranged from 0.838 to 0.954,

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and α values ranged from 0.709 to 0.928, all surpassing the acceptable threshold of 0.70 and thereby confirming good to excellent reliability across all constructs.

Discriminant validity was assessed using the Heterotrait-Monotrait Ratio of Correlations (HTMT). All HTMT values were below the conservative cutoff of 0.85, with the upper bound of the 95% confidence interval remaining below 1.00. This pattern confirms that the constructs are empirically distinct from one another. Collectively, these psychometric properties satisfy the prerequisites for proceeding to structural model evaluation.

Descriptive Statistics and Correlations

Table 3. Descriptive statistics and correlations between variables

Variable	M	SD	Correlations		
			1	2	3
Digital Competence	0.397	0.077			
Learning Style	0.211	0.053	0.689***		
Self-Determined Learning (SDL)	0.642	0.047	0.798***	0.724***	
Attitudes towards Flipped Learning	0.632	0.040	0.742***	0.589***	0.584***

*Note. *** p < .001. Values represent standardized latent variable scores derived from the PLS-SEM algorithm.*

Table 3 reports the latent variable means, standard deviations, and Pearson correlation coefficients. It should be noted that the values presented represent standardized latent variable scores derived from the PLS-SEM algorithm, rather than raw Likert scale means. The highest mean scores were observed for Self-Determined Learning (M = 0.642, SD = 0.047) and Attitudes toward Flipped Learning (M = 0.632, SD = 0.040), suggesting that respondents generally reported high levels of learning agency and favorable attitudes toward the flipped approach. Digital Competence (M = 0.397, SD = 0.077) and Learning Style (M = 0.211, SD = 0.053) exhibited comparatively lower mean values. The relatively small standard deviations indicate moderate homogeneity in the distribution of latent scores across the sample.

All bivariate correlations were positive and statistically significant at $p < .001$. The strongest association was found between SDL and DC ($r = .798$), followed by DC and SFLIPP ($r = .742$), and SDL and LS ($r = .724$), all representing large effect sizes. The correlation between DC and LS was also substantial ($r = .689$), whereas the relationships between LS and SFLIPP ($r = .589$) and SDL and SFLIPP ($r = .584$) were in the medium to large range.

Structural Model and Hypothesis Testing

The structural model demonstrated moderate predictive capability. The model explained 39.8% of the variance in Digital Competence, 41.2% of the variance in Learning Style, and 42.7% of the variance in Attitudes toward Flipped Learning, indicating acceptable explanatory power.

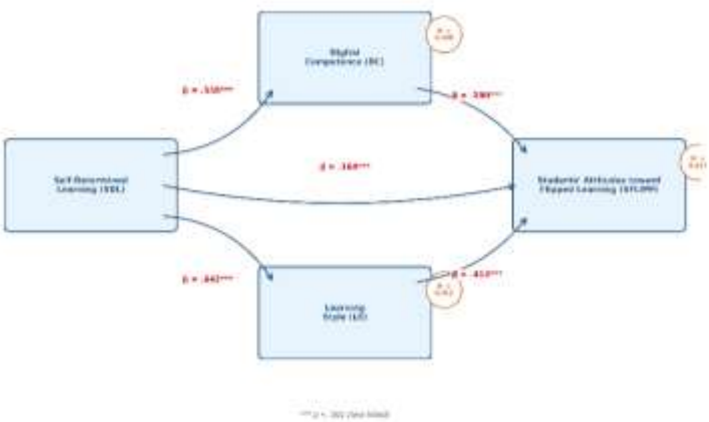

Figure 1. PLS-SEM Structural Model with Standardized Path Coefficients

Direct effects. All direct paths in the structural model were positive and statistically significant ($p < .001$). The path coefficient from Learning Style to SFLIPP was the strongest (β = .413), followed by Digital Competence to SFLIPP (β = .190), and Self-Determined Learning to SFLIPP (β = .164). In the antecedent portion of the model, SDL exerted strong positive effects on both mediators: SDL → LS (β = .642) and SDL → DC (β = .558).

Table 4. Direct, Indirect, and Total Effects of Paths in the Model

Path	Direct Effect	Indirect Effect	Total Effect	P Values
LS → SFLIPP	0.413	—	0.413	< .001
DC → SFLIPP	0.190	—	0.190	< .001
SDL → LS	0.642	—	0.642	< .001
SDL → DC	0.558	—	0.558	< .001
SDL → SFLIPP	0.164	—	0.535	< .001
SDL → LS → SFLIPP	—	0.265	—	< .001
SDL → DC → SFLIPP	—	0.106	—	< .001

Indirect effects and mediation analysis. Two significant indirect effects of SDL on SFLIPP were identified. The indirect effect via Learning Style was β = .265 ($p < .001$), and the indirect effect via Digital Competence was β = .106 ($p < .001$). The total effect of SDL on SFLIPP amounted to β = .535 ($p < .001$), comprising the direct effect (β = .164) and the two indirect effects. The proportion of the total SDL effect mediated through the two intervening variables was approximately 69.3%. Of this mediated portion, the pathway through Learning Style accounted for roughly 71.4%, while the pathway through Digital Competence contributed approximately 28.6%. Because the direct path from SDL to SFLIPP remained statistically significant after the inclusion of mediators, the mediation pattern is classified as partial mediation, with Learning Style serving as the dominant mediator.

Discussion

The present study set out to examine how Self-Determined Learning, Digital Competence, and Learning Style collectively shape students' attitudes toward flipped learning through an integrated structural model. The findings provide substantial empirical support for the hypothesized pathways and offer several theoretical and practical insights.

The strong predictive power of Learning Style (LS) on attitudes toward flipped learning (β = .413) underscores the critical importance of *person–method fit* in technology-mediated pedagogies. This finding suggests that when students' innate learning preferences—whether collaborative or individual, autonomous or guided—align with the structural demands of flipped learning (self-paced pre-class preparation followed by collaborative, problem-based face-to-face sessions), their attitudinal evaluations become significantly more favorable. This result is consistent with the Felder-Silverman Index of Learning Styles framework, which posits that instructional compatibility with learner preferences enhances engagement and comfort (Felder & Spurlin, 2005). It also reinforces the broader pedagogical principle that differentiated instruction, which accommodates diverse learner profiles, is essential for optimizing attitudinal outcomes in non-traditional learning environments (Koh, 2019).

The significant yet comparatively smaller direct effect of Digital Competence (DC) on SFLIPP (β = .190) aligns with the predictions of the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT), which identify perceived usefulness and ease of use as core determinants of technology acceptance (Venkatesh & Davis, 2000; Alyoussef, 2022). However, it is noteworthy that while the bivariate correlation between DC and SFLIPP was strong ($r = .742$), its unique structural contribution was attenuated when the shared variance with SDL and LS was accounted for. This pattern suggests that digital competence in the flipped learning context is not an isolated technical skill but is often embedded within broader self-regulatory dispositions and learning preferences. Students who are already self-determined and possess adaptive learning styles are more likely to translate their digital proficiency into positive attitudinal evaluations of flipped instruction. This finding resonates with the European Digital Competence Framework, which conceptualizes digital literacy as an integrated competency that operates most effectively when coupled with autonomy and purposeful learning behavior (Ilomäki et al., 2016; Vuorikari et al., 2016).

The Self-Determined Learning (SDL) findings offer compelling evidence for the centrality of student agency in the flipped learning ecosystem. The substantial total effect of SDL on SFLIPP ($\beta = .535$) confirms that self-determined learners those who set clear objectives, engage in reflective planning, and evaluate their own understanding are significantly more inclined to hold positive attitudes toward flipped learning. This result is theoretically grounded in Self-Determination Theory (SDT), which posits that autonomy, competence, and relatedness are fundamental psychological nutrients that foster intrinsic motivation and adaptive engagement (Ryan & Deci, 2000). Furthermore, the strong effects of SDL on both LS and DC suggest that self-determination functions as a foundational disposition that cascades into both technological readiness and learning preference adaptability. This cascading mechanism is consistent with heutagogical principles, which emphasize self-directed agency as the cornerstone of lifelong learning capability (Blaschke, 2012; Amiruddin et al., 2022).

The mediation analysis reveals a particularly important insight: the majority of SDL's influence on attitudes operates *indirectly* rather than directly. With nearly 70% of the total effect being mediated, the model demonstrates that self-determined learning does not merely translate into favorable attitudes in a vacuum; rather, it does so by fostering learning style compatibility and digital competence. The dominance of the LS-mediated pathway (accounting for ~71% of the mediated effect) over the DC-mediated pathway (~29%) suggests that in the context of flipped learning, pedagogical preference alignment may be a more potent attitudinal lever than technological proficiency alone. This finding carries significant implications for instructional design: while equipping students with digital tools is necessary, ensuring that the pedagogical structure resonates with their learning preferences is arguably more consequential for cultivating positive attitudes.

From a cognitive load and motivation perspective, the findings corroborate the theoretical assertion that flipped learning can enhance engagement and manage cognitive load effectively, but only when the prerequisites for independent learning are satisfied (Abeysekera & Dawson, 2015). The high mean score for SDL ($M = 0.642$) suggests that the present sample was relatively well-prepared for self-directed pre-class engagement, which likely contributed to the overall positive attitudinal profile. This aligns with empirical evidence indicating that self-regulation support embedded in pre-class materials such as explicit goal-setting, reflective prompts, and diagnostic warm-up activities significantly improves learning outcomes in flipped environments (van Alten et al., 2020).

The high correlation between SDL and DC ($r = .798$) observed in this study warrants careful interpretation. While PLS-SEM is designed to handle correlated constructs, this level of association suggests substantial conceptual overlap between self-directed learning dispositions and digital tool usage. It indicates that digital competence in this sample may partly be an expression of self-regulated learning behavior rather than a purely technical skill. This finding is not entirely surprising, as self-determined learners are naturally more inclined to explore and master digital tools for learning. Future research may consider higher-order modeling or collinearity diagnostics (e.g., full collinearity VIF) to further disentangle these constructs (Kock, 2015). Nevertheless, the HTMT values remained within acceptable bounds, and the discriminant validity of the measurement model was supported.

Practical Implications.

The findings distill into three actionable design principles for educators. First, strengthening SDL should be prioritized through the implementation of learning contracts, explicit pre-class objectives, reflective journaling prompts, and low-stakes diagnostic quizzes. These strategies not only cultivate agency but also establish the self-regulatory foundation necessary for successful flipped learning (Abeysekera & Dawson, 2015; van Alten et al., 2020). Second, differentiating instruction according to learning style profiles can maximize person–method fit. Instructors might design pre-class activities that allow for individual mastery attempts, followed by carefully orchestrated, problem-based collaborative sessions during face-to-face meetings (Koh, 2019). Third, raising the baseline of responsible digital competence remains essential. This can be achieved through brief LMS and video conferencing orientations, micro-training modules on information literacy, and ethical guidelines for AI-assisted learning (e.g., using ChatGPT for material exploration rather than academic shortcutting). Such interventions are consistent with the Digital Competence Framework and the broader literature on technology acceptance in education (Alyoussef, 2022; Tlili et al., 2023; Vuorikari et al., 2016).

Limitations and Future Directions

Several limitations should be acknowledged. First, the cross-sectional design precludes causal inferences; the relationships identified are correlational and simultaneous, not longitudinal. Second, the sample was predominantly drawn from the Faculty of Engineering (57.22%), which limits the generalizability of findings to students in humanities, social sciences, or health sciences. Third, the operationalization of Learning Style was limited to three behavioral indicators and did not capture the full multidimensionality of the Felder-Silverman ILS model. Fourth, the high correlation between SDL and DC raises potential common method bias concerns, although the measurement model exhibited acceptable discriminant validity. Future research should employ longitudinal designs, stratified sampling across disciplines, and more comprehensive learning style instruments to validate and extend the present findings.

CONCLUSIONS

This study confirms that students' attitudes toward flipped learning are shaped by an integrated interplay of Self-Determined Learning, Digital Competence, and Learning Style. The structural model demonstrated that Learning Style is the strongest direct predictor of favorable attitudes, while Self-Determined Learning exerts its influence primarily through indirect pathways—most dominantly via Learning Style compatibility. These findings underscore that successful flipped learning implementation requires a holistic instructional approach: strengthening pre-class self-regulation through explicit goals and reflective scaffolds, differentiating activities to align with diverse learning preferences, and cultivating responsible digital literacy through targeted training and ethical AI guidelines. Future research should employ longitudinal and cross-disciplinary designs to further validate this integrative framework.

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AUTHOR CONTRIBUTION STATEMENT

MHR conceptualized the research design, supervised the study, performed data collection and analysis, wrote the original draft, and served as the corresponding author. A contributed to methodology validation and critical review of the study. N contributed to the review and editing of the manuscript. All authors approved the final version of the manuscript.

AI DISCLOSURE STATEMENT

The authors used Kimi (Moonshot AI) during the preparation of this manuscript for language editing and improving clarity and structure. After using this tool, the authors thoroughly reviewed and revised the content as necessary and take full responsibility for the integrity and accuracy of the publication.

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