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Digital Technology and Reading Habits of Students: An Empirical Study Using A Structural Equation Model

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Abstract

Digital technology is restructuring how students access knowledge and form reading habits in higher education. However, research on this topic has revealed such gaps as (a) a lack of integrated models simultaneously encompassing digital learning environments, library support, and information behaviour within a single structural validation framework; (b) a lack of studies from educational institutions in Southeast Asia; and (c) a failure to separate the mediating roles between these factors. This study surveyed 853 students at Hanoi Open University in August 2025, using the Partial Least Squares Structural Equation Model (PLS-SEM) to test five direct relationships and two mediating relationships. The results showed that (a) the digital learning environment (DIG) had a positive impact on information behaviour (INF) ($\beta = 0.420$) and academic reading engagement (ARE) ($\beta = 0.280$); (b) library support (LIB) had a positive impact on information behaviour ($\beta = 0.310$); and (c) information behaviour had a positive impact on academic reading ($\beta = 0.390$). The direct LIB → ARE path was not significant ($\beta = 0.057$; ns), confirming indirect-only information-mediated behaviour. The model explained 51.2% of the dependent variable variance. The average reading time was 3.91 hours a week (95% confidence interval (CI) [3.79; 4.03]), which was lower than referenced international studies, although direct comparisons were limited by differences in measurement methods. The digital entertainment time-to-academic reading time ratio of 5.7:1 is consistent with the media displacement theory. The study proposes repositioning the function of university libraries from resource gateway to orchestrator of reading behaviour.

Keywords: digital technology, information behaviour, open higher education, PLS-SEM, reading habits, students

1. Introduction

The rapid development of digital technology has fundamentally shaped how students access and process information in higher education. The internet, mobile devices, online learning platforms, and social media have shifted the focus of learning materials from print to digital sources. In the Organisation for Economic Co-operation and Development (OECD) Programme for International Student Assessment (PISA) 21st-Century Readers report (Organisation for Economic Co-operation and Development, 2021), 86% of students in OECD countries claimed to read news, texts, or documents on digital devices at least once a week.

This shift speaks of more than just the medium. Cognitive and educational neuroscience studies show that screen reading is associated with changes in attention structure, processing depth, and critical thinking abilities (Wolf, 2018; Carr, 2010). Two large-scale meta-analyses, i.e., by Delgado et al. (2018, k = 54 studies) and Clinton (2019, k = 33 studies), both confirmed a small but consistent effect: reading on paper leads to better in-depth understanding than reading on screen, especially with long texts and time pressure.

Besides effects on reading activity, digital technology, through social media and entertainment platforms, also creates temporal competition for academic reading. According to the media displacement theory, as new media emerges and time allocation is finite, new media will replace or reduce the time spent on older media. Saaid and Wahab (2014), Mirza et al. (2021), and Annisette and Lafreniere (2017) provide empirical evidence for this effect in different contexts.

However, existing works reveal remaining gaps in research on this issue. First, most empirical research focuses on Western or developed East Asian contexts (Mizrachi et al., 2021); evidence from developing Southeast Asian countries is fragmented and lacks integrated models. Second, studies often examine individual factors, either the digital environment, reading behaviour, or the role of the library, without simultaneously integrating all three within a structured testing framework. This leads to a lack of clarity regarding the order of influence and mediating roles. Third, most research is conducted on full-time university students; students in open and distance learning (ODL) institutions, as members of a group characterised by high digital technology use and flexible learning schedules, have not been adequately studied.

Thus, this empirical study at Hanoi Open University (HOU), Vietnam's leading ODL institution, was designed with three specific objectives: (a) to analyse the current state of reading habits and level of digital technology use of students in an open learning environment; (b) to build and test a Partial Least Squares Structural Equation Model (PLS-SEM) integrating the digital environment, library support, and information behaviour that influences academic reading participation, with a mediating role test; and (c) to propose theoretical and practical implications for developing a reading culture in an open higher education environment.

2. Literature Review

2.1. Reading in the Digital Environment: Media Shift and Cognitive Change

Reading is a complex cognitive activity requiring coordination between character recognition, language processing, working memory, and attention control. Wolf (2018) argues that the brain does not have an innate reading circuit; this circuit is constructed through training and can be restructured by the dominant reading environment. When students primarily read short, nonlinear digital texts with distracting hyperlinks and advertisements, they inadvertently train a reading circuit that prioritises speed and multitasking rather than deep reading.

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Empirical evidence for this is fairly consistent. Mangen et al. (2013) found lower plot comprehension when reading on a computer compared to reading the same content on paper. Singer and Alexander (2017) confirmed the advantage of paper for deep comprehension, especially with texts that have complex argumentative structures. Two meta-analyses by Delgado et al. (2018) and Clinton (2019) quantified this effect with Hedges' g ranging from -0.21 to -0.29, indicating a small but consistent advantage for paper-based reading.

However, digital reading is not entirely linked to negative attributes. Liu (2005) points out that digital reading is suitable for information-driven searching (e.g., browsing, scanning), while paper reading is more suitable for extended reading and reflection. Baron (2021) develops this idea into a strategic choice recommendation: 21st-century reading ability lies in the ability to choose the medium appropriate to cognitive goals. More recent evidence reinforces this nuanced picture. Altamura et al. (2025), in a meta-analysis of 40 effect sizes covering 469,564 participants, found that leisure digital reading habits are only weakly associated with text comprehension ($r = .055$), a far smaller relationship than the one long documented for print reading habits. Sackstein et al. (2015) likewise reported differences in reading speed and comprehension between tablet and paper formats, indicating that the medium continues to shape how efficiently students process academic texts.

These findings suggest that pedagogical interventions, rather than medium-switching alone, may be the most effective response to screen-reading challenges in a higher education context such as that at HOU.

2.2. Information Behaviour of Students in the Digital Environment

Information behaviour includes searching, evaluating, organising, and using information. It serves as the intermediate link between the information environment and learning activities (Wilson, 1999). It is important to distinguish information behaviour from information literacy: information behaviour is a descriptive concept referring to the full range of activities through which people seek, encounter, and use information (Wilson, 1999; Case & Given, 2016), whereas information literacy is a normative, competency-based concept referring to the ability to recognise when information is needed and to locate, evaluate, and use it effectively (Association of College and Research Libraries [ACRL], 2016; Bawden & Robinson, 2022). In this study, the information behaviour (INF) construct operationalises what students actually do when seeking and using information, rather than their level of information literacy competence. This distinction matters theoretically: low information literacy may explain why some students engage in information behaviour (e.g., searching) without achieving deep reading outcomes, which is consistent with the indirect-only mediation found for the library support (LIB) → academic reading engagement (ARE) relationship.

Two characteristic phenomena are information overload and attention dispersion. Bawden and Robinson (2009) argue that information overload is not a matter of quantity but of processing capacity: when accessibility skyrockets but evaluation skills do not keep pace, users rely on surface signals (e.g., likes, search result position) instead of source reliability. Salmerón et al. (2018) add that notifications, multitasking, and multi-window environments reduce text processing depth.

Ogunbodede and Sawyerr-George’s (2023) survey of Nigerian university students found that heavy reliance on digital resources coincided with limited sustained academic reading, a pattern attributed to the ease with which brief, fragmented online material displaces extended engagement. Nguyen and Tuamsuk (2023) reported a comparable pattern in Vietnamese universities: although institutions, libraries, and lecturers had put digital resources and supporting regulations in place, the factors that most strongly shaped digital reading were those relating to students and lecturers themselves, underscoring the need for intentional design of digital learning environments rather than resource provision alone.

2.3. Theoretical Framework: Media Displacement and Planned Behaviour

The media displacement theory (Williams, 1986) argues that because time is a finite resource, a new media outlet occupying this limited resource will inevitably reduce the time spent on existing media, with this effect being stronger when the two media outlets serve the same functional needs. In higher education, social media and academic reading compete for free time despite fulfilling different needs; Annisette and Lafreniere (2017) provide quantitative evidence for this effect.

However, in the higher education context, some considerations are necessary, such as the fact that the displacement effect operates between academic reading and digital entertainment (e.g., social media, videos, games) rather than between academic reading and digital learning resource environments (e.g., learning management systems (LMS), e-books, academic databases) that support learning. In this study, the digital learning environment (DIG) variable measures the digital learning environment (which is expected to have a positive impact on academic reading), while the shift to digital entertainment is described in Section 4.4.

Furthermore, the study uses the theory of planned behaviour (TPB) (Ajzen, 1991) as an auxiliary framework. According to the TPB, behaviour is predicted by attitude, subjective norms, and perceived behavioural control. This theoretical framework can be applied to explain the attitude-behaviour gap when students positively evaluate a resource such as a library but do not actually use it. The TPB complements media migration at the micro level: it helps explain why the same digital learning environment produces different levels of migration among students, and why investment in library infrastructure needs to be accompanied by information literacy training to increase perceived behavioural control.

2.4. Research Model and Hypotheses

Based on the theoretical framework and the gaps mentioned above, we propose a model that consists of four latent variables and six hypotheses. Importantly, this model excludes the digital entertainment environment.

The four latent variables are as follows:

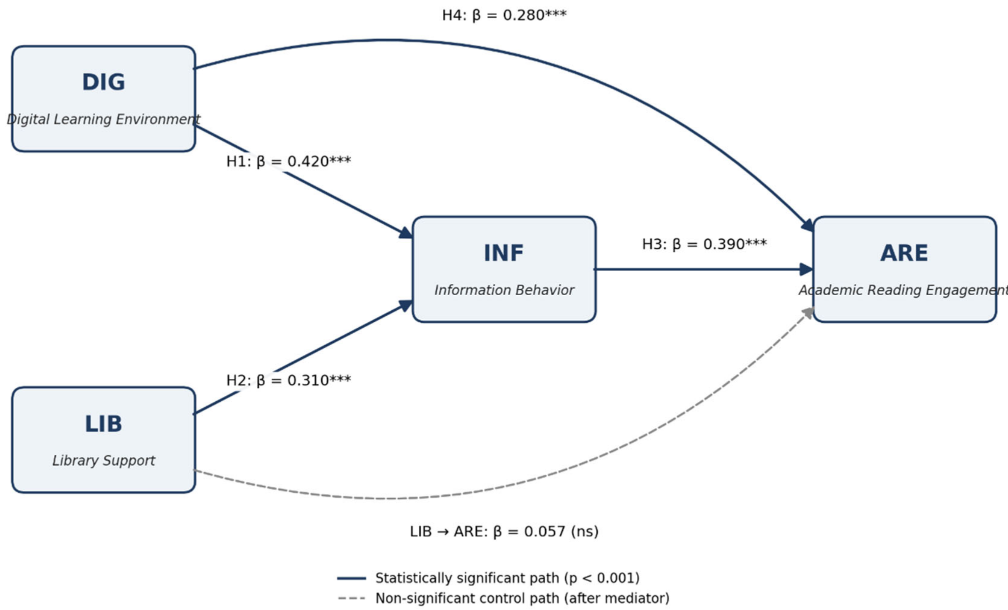
1. DIG measures the level of integration and use of learning resource platforms such as LMS, e-books, academic databases, and online learning tools,
2. LIB measures the ability to provide resources and information literacy training,
3. INF, a mediating variable, reflects how students find, evaluate, and use information, and
4. ARE is the dependent variable used to measure the frequency, duration, and depth of reading activity.

The six hypotheses are as follows:

1. H1: DIG positively influences INF.
2. H2: LIB positively influences INF.
3. H3: INF positively influences ARE.
4. H4: DIG directly positively influences ARE.
5. H5: INF mediates the DIG → ARE relationship.
6. H6: INF mediates the LIB → ARE relationship.

Figure 1

Research Model and Tested Hypotheses



Note. The solid dark-blue lines indicate statistically significant paths ($p < 0.001$) corresponding to hypotheses H1 through H4. The dashed grey line is the LIB → ARE control path included to classify mediation type following Zhao et al. (2010); the non-significant result ($\beta = 0.057$; ns) supports the conclusion that information behaviour plays an indirect-only mediating role for the LIB → ARE relationship. The two indirect effects DIG → INF → ARE and LIB → INF → ARE were tested using bootstrapping with 5,000 resamples.

3. Research Methodology

3.1. Research Design

This study employs a cross-sectional quantitative design, using a structured questionnaire survey. The model was validated using the PLS-SEM via SmartPLS 4.0 software. The PLS-SEM was chosen because it is suitable for models with mediating variables, less sensitive to the assumption of normal distribution compared to a covariance-based model (i.e., CB-SEM), and optimal for medium-to-large sample sizes with the same exploratory objectives (Hair et al., 2022).

3.2. Participants and Sample

The study population comprised students currently enrolled at HOU, which is the largest ODL institution in Vietnam with a relatively well-developed digital learning resource system. The study employed a non-probability convenience sampling technique combined with proportional stratified sampling by faculty/institute. The strata were defined according to three main disciplinary groups (i.e., social sciences, economics, and technology-engineering) and year of study. Respondents were recruited proportionally within each stratum to ensure diversity across academic disciplines and years of study. This combined technique was adopted because a complete sampling frame of the ODL student population was not available, while stratification helped reduce coverage bias across faculties.

In terms of sample size, the rule of 10 times the largest number of arrows pointing to a latent variable (Hair et al., 2022) provides a minimum threshold of 20 because the INF variable receives two arrows. To ensure estimation stability and detect small effects, the study also applied Comrey and Lee's (1992) criterion, which considers a threshold of ≥500 as very well-ranked. The actual sample size of N = 853 exceeded this threshold.

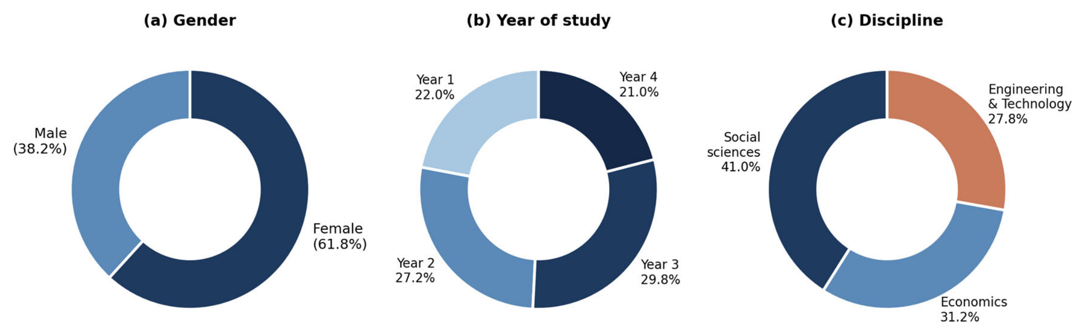
A total of 990 questionnaires were received in August 2025. After removing 137 invalid questionnaires (i.e., those missing more than 10% of the questions, showing signs of rote answering on straight-lining, or completed in fewer than 60 seconds), 853 questionnaires were used in the analysis, which was a completion rate of 86.2%. Since the online survey did not define a sampling frame, this is considered the completion rate, not the response rate. The demographic characteristics of the sample are presented in Table 1.

3.3. Measurement Instrument

The questionnaire comprised five sections with a total of 27 questions, of which 22 measured the four latent variables on a five-point Likert scale describing a range of scores between one ('Strongly disagree') and five ('Strongly agree'). The scales were preliminarily tested with 30 students before official implementation. Demographic characteristics and the measurement structure are presented in Figure 2 and Table 1.

Figure 2

Sample Composition by Gender, Year of Study, and Discipline (N = 853)



Source. Authors' analysis based on the survey data (N = 853).

Table 1

Measurement Structure and Scale Sources

Latent variable	Number of items	Item codes	Source of scale
DIG	6	DIG1-DIG6	Adapted from Liu (2005), Mizrachi et al. (2021)
LIB	6	LIB1-LIB6	Adapted from Borgman (2007), ACRL (2016)
INF	5	INF1-INF5	Adapted from Wilson (1999), Mizrachi et al. (2021)
ARE	5	ARE1-ARE5	Adapted from Pecorari et al. (2012), Wolf (2018)

Note. DIG = digital learning environment; LIB = library support; INF = information behaviour; ARE = academic reading engagement.

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3.4. Data Collection Procedures and Research Ethics

Data were collected using Google Forms over three weeks in August 2025. The questionnaire was distributed through HOU's LMS, official student email, and channels managed by the student union. Students participated voluntarily, were informed of the purpose, as well as their rights to withdraw and to remain anonymous. The study did not collect identifying information; data was stored on a password-protected system and accessed only by the research team.

3.5. Data Analysis

The analysis consisted of five steps. First, descriptive statistics were performed along with outliers testing via Mahalanobis distance ($p < 0.001$) and distribution assumptions via skewness ($|\cdot| < 3$) and kurtosis ($|\cdot| < 7$) (Kline, 2016). Next, the measurement model was evaluated with thresholds Cronbach's alpha $\alpha \geq 0.7$; Composite Reliability (CR) ≥ 0.7; loading ≥ 0.5; Average Variance Extracted (AVE) ≥ 0.5; and heterotrait-monotrait ratio of correlations (HTMT) < 0.85.

The third step was a supplemental exploratory factor analysis (EFA) with Promax rotation (Kaiser–Meyer–Olkin (KMO ≥ 0.6; Bartlett's test $p < 0.05$; variance ≥ 50%). The oblique rotation was chosen instead of the Varimax rotation because the latent variables have causal relationships (DIG → INF, LIB → INF, INF → ARE). Thus, expecting correlation, the orthogonality assumption was not satisfied (Costello & Osborne, 2005; Field, 2018). Step four evaluated the structural model with the variance inflation factor (VIF) < 5; bootstrap 5,000 samples; percentile confidence interval (CI); R^2; $Q^2 > 0$; standardised root mean square residual (SRMR) ≤ 0.08. Finally, mediating effects were tested through bootstrapping with 5,000 samples and classified according to Zhao et al. (2010).

3.6. Common Method Bias Control

To mitigate the common method bias (CMB), preventive measures following Podsakoff et al. (2003) were taken, including ensuring anonymity, reordering the questionnaire groups, and using different scale labels. After data collection, three classes of tests were conducted. Harman's single-factor test (threshold < 50%) was only reported as a reference due to sensitivity limitations pointed out by Podsakoff et al. (2003). The primary measure was the unmeasured latent method construct (ULMC) according to Liang et al. (2007) and Williams and McGonagle (2016); the model was further estimated with a latent method variable loaded by all 22 indicators, and then a comparison of the structural impact path was done before and after adding the method factor. Finally, the inner VIF (threshold < 3.3, based on Kock, 2015) served as an auxiliary indicator of intrinsic multicollinearity due to the CMB.

4. Findings and Discussion

4.1. Sample Characteristics

The sample N = 853 has a relatively balanced distribution with females representing 61.8% (n = 527) while males accounted for 38.2% (n = 326). Students in their second and third years of study account for the largest proportion at 57%, while the breakdown by faculty was 41.0% (social sciences), 31.2% (economics), and 27.8% (technology-engineering) (see Figure 2).

4.2. Measurement-Model Evaluation

Before validating the structural model, the quality of the measurement model was assessed through reliability and validity indicators. The results are shown in Table 2.

Table 2

Reliability and Convergent Validity of the Latent Variables

Latent variable	Number of items	Loadings (range)	Cronbach's α	CR	AVE
DIG	6	0.68 - 0.84	0.832	0.876	0.545
LIB	6	0.71 - 0.86	0.851	0.889	0.572
INF	5	0.69 - 0.82	0.807	0.861	0.553
ARE	5	0.72 - 0.87	0.846	0.891	0.621

Note. DIG = digital learning environment; LIB = library support; INF = information behaviour; ARE = academic reading engagement; CR = Composite Reliability; AVE = Average Variance Extracted. All variables meet the following thresholds: α ≥ 0.7; CR ≥ 0.7; AVE ≥ 0.5 (Hair et al., 2022).

Discriminant validity was tested using two supplementary criteria. First, the HTMT criterion recommended by Henseler et al. (2015), used as the primary criterion for the PLS-SEM, showed that all HTMT values were below the threshold of 0.85. The highest value was 0.72 between DIG and INF (see Table 3a). Second, the Fornell-Larker criterion (Fornell & Larcker, 1981), requiring the square root of the AVE of each latent variable to be greater than the correlation of that variable with any other latent variable, was also used. All variables satisfied this condition (see Table 3b). Both criteria confirmed that the latent variables were distinct from each other.

Table 3a

HTMT Matrix

Latent variable	DIG	LIB	INF	ARE
DIG	-			
LIB	0.58	-		
INF	0.72	0.64	-	
ARE	0.68	0.55	0.71	-

Note. HTMT threshold < 0.85 (Henseler et al., 2015). All values are below this recommended threshold.

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Table 3b

Fornell-Larcker Matrix

Latent variable	DIG	LIB	INF	ARE
DIG	**0.738**			
LIB	0.521	**0.756**		
INF	0.649	0.576	**0.744**	
ARE	0.609	0.494	0.638	**0.788**

Note. The diagonal values (in bold) are the square root of the AVE; underneath the diagonal cells are correlations between latent variables. The Fornell and Larcker (1981) criterion requires that the diagonal value (√AVE) exceeds all correlations of that variable with the others. All four variables satisfy this criterion (DIG: 0.738 > 0.649; LIB: 0.756 > 0.576; INF: 0.744 > 0.649; ARE: 0.788 > 0.638).

An auxiliary EFA with Promax rotation yielded the following results: KMO = 0.887 (considered very good); Bartlett's test was statistically significant (χ^2 = 9,247.3; df = 231; $p < 0.001$); four factors were extracted with a cumulative explanatory variance of 64.3% (exceeding the 50% threshold); the pattern matrix showed that all items loaded the correct theoretical factors with coefficients ≥ 0.5 and there was no cross-loading. The correlation between factors in the factor correlation matrix ranged from 0.46 to 0.68. This confirms the assumption that the latent variables are correlated and justifies the choice of oblique rotation instead of orthogonal rotation.

4.3. CMB Testing

CMB was assessed using three measures. First, Harman's single-factor test (reference report) showed that the first factor explained 32.7% of the variance, below the 50% threshold. Second, the ULMC was the primary measure according to Liang et al. (2007): the supplementary model was estimated with a common latent method variable that all 22 indicators loaded together; the average factor load on the theoretical variable was 0.756 (average theoretical $R^2 \approx 0.572$), while the average factor load on the method variable was only 0.082 (average method $R^2 \approx 0.007$), demonstrating that the proportion of variance explained by the theoretical variable was approximately 82 times higher than the variance explained by the method variable, far exceeding the 10:1 threshold proposed by Williams and McGonagle (2016). Comparison of path coefficients between the original model and the model with ULMC showed a maximum change of $\Delta\beta = 0.031$ (DIG → INF). This means it is below the threshold of 0.05, which is commonly used as a criterion for assessing the significant impact of CMB. Third, the inner VIF of the latent variables ranged from 1.42 to 2.18, all below the threshold of 3.3 (Kock, 2015). All three measures consistently indicated that CMB was not a significant threat to the structural results of the study.

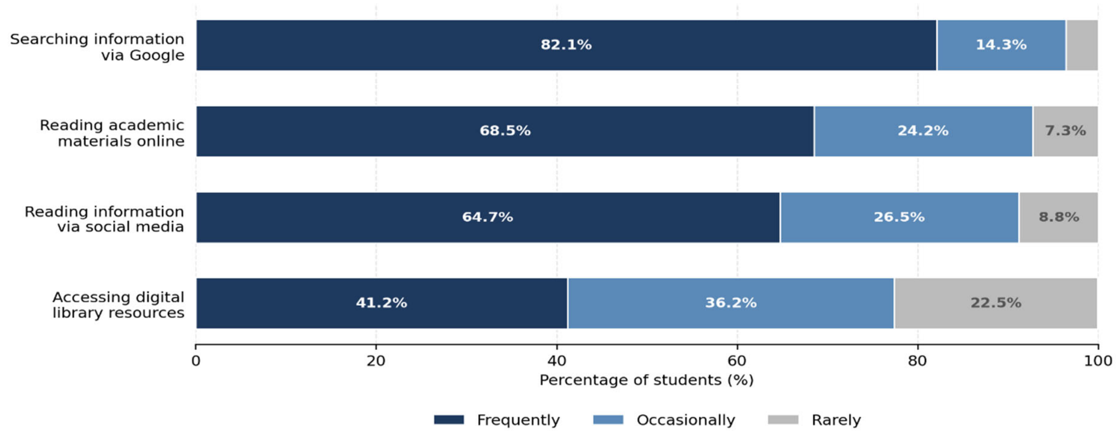
4.4. Reading Habits and Use of Digital Technology

Students demonstrate a positive attitude towards reading, but their actual reading time is limited, averaging only 3.91 hours per week (M = 3.91; SD = 1.87; 95% CI [3.79; 4.03]) and appearing to prioritise digital learning materials (i.e., lecture slides, electronic documents, online resources) over printed books. The main purpose of reading, therefore, is for learning, while reading for personal knowledge enhancement or entertainment accounts for a smaller percentage.

Reading and information retrieval behaviour in the digital environment is presented in Figure 3. The data shows that the popular search engine Google is the dominant source of information retrieval (82.1%); reading online academic materials accounts for 68.5%; using social networks accounts for 64.7%; while accessing digital resources from the library only accounts for 41.2%, which is lower than the popular channels.

Figure 3

Frequency of Digital Reading and Information-Seeking Activities (N = 853)

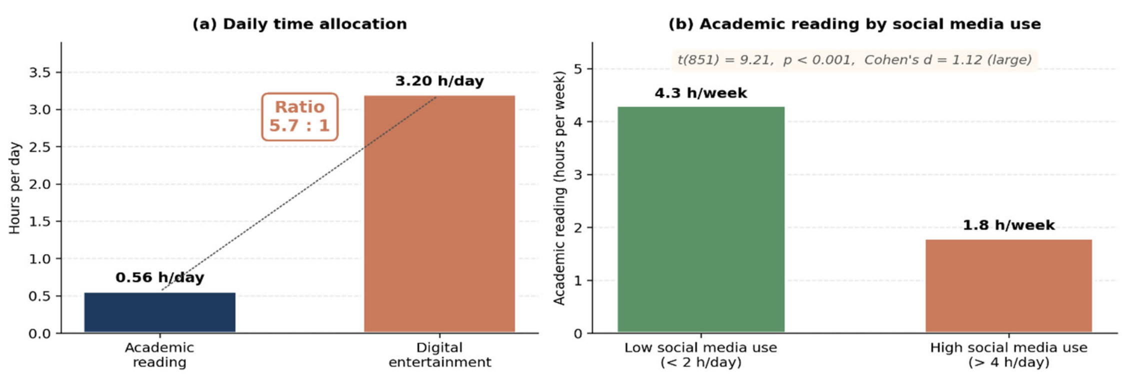


Source. Authors' analysis based on the survey data (N = 853). Frequency was self-reported by students on a three-point scale.

Regarding the competition for time between reading digital materials and digital entertainment, it was found that students spend an average of 3.2 hours daily on social media and digital entertainment, compared to only 0.56 hours daily on reading. This yields a ratio of approximately 5.7:1. As many as 52.3% of students spend more than three hours daily on digital entertainment; 77% read fewer than three hours a week; and 59.4% acknowledge that entertainment technology reduces their reading time. The group using social media for more than four hours daily reads an average of 1.8 hours weekly, significantly lower than the group spending fewer than two hours daily on social media (i.e., 4.3 hours per week). Independent t-tests confirmed these statistically significant differences ($t(851) = 9.21$; $p < 0.001$; Cohen's d = 1.12).

Figure 4

Time Competition Between Academic Reading and Digital Entertainment

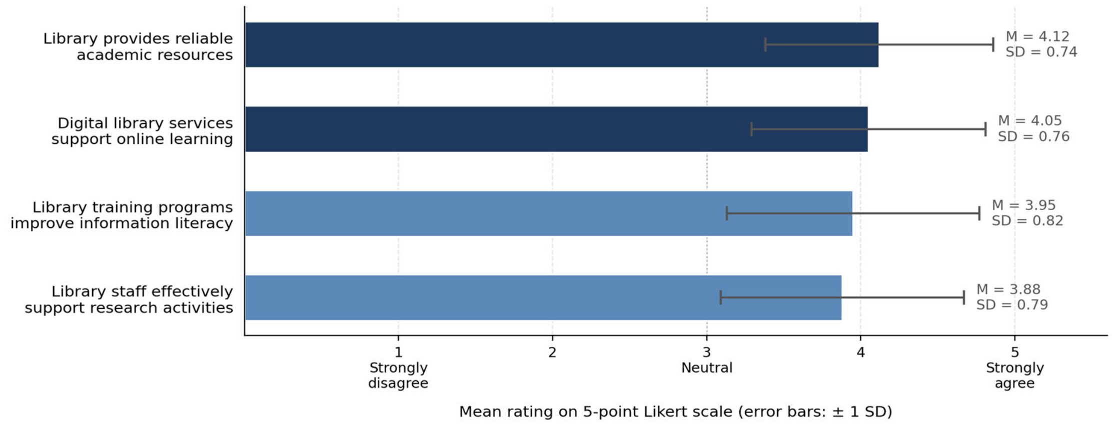


Source. Authors' analysis based on the survey data (N = 853). (a) Comparison of average daily time; (b) Comparison of weekly reading time between two social-media-use groups via an independent-samples t-test.

Regarding the perceived role of the library, students highly rated its function of providing reliable resources (M = 4.12; SD = 0.74), and digital library services supporting learning (M = 4.05; SD = 0.76). However, the functions of training information literacy (M = 3.95; SD = 0.82) and supporting research by library staff (M = 3.88; SD = 0.79) were given lower scores (Figure 5).

Figure 5

Student Perceptions of the Role of the University Library (N = 853)



Source. Authors' analysis based on the survey data (N = 853) on a five-point Likert scale (1 = Strongly disagree; 5 = Strongly agree). Error bars represent ± 1 SD.

4.5. Structural Model and Hypothesis Testing

The structural model was validated using the PLS-SEM with a bootstrap of 5,000 replicates. The overall model fit indices were good: SRMR = 0.067 (≤ 0.08); NFI = 0.924 (≥ 0.9); d_ULS and d_G were below the 95% bootstrap threshold (Hair et al., 2022). In addition to the four hypothesised impact pathways (H1–H4), the model included an additional direct pathway LIB → ARE to provide a basis for correctly classifying the intermediate type according to Zhao et al. (2010). The results of the five direct pathways are presented in Table 4.

Table 4

Results of Direct-Hypothesis Testing

Hyp.	Relationship	Standardized β	SE	t-statistic	95% CI	Conclusion
H1	DIG → INF	0.420***	0.038	11.05	[0.344; 0.493]	Supported
H2	LIB → INF	0.310***	0.041	7.56	[0.229; 0.389]	Supported
H3	INF → ARE	0.390***	0.043	9.07	[0.305; 0.473]	Supported
H4	DIG → ARE	0.280***	0.045	6.22	[0.191; 0.367]	Supported
Control	LIB → ARE	0.057	0.047	1.21	[-0.034; 0.148]	Not significant

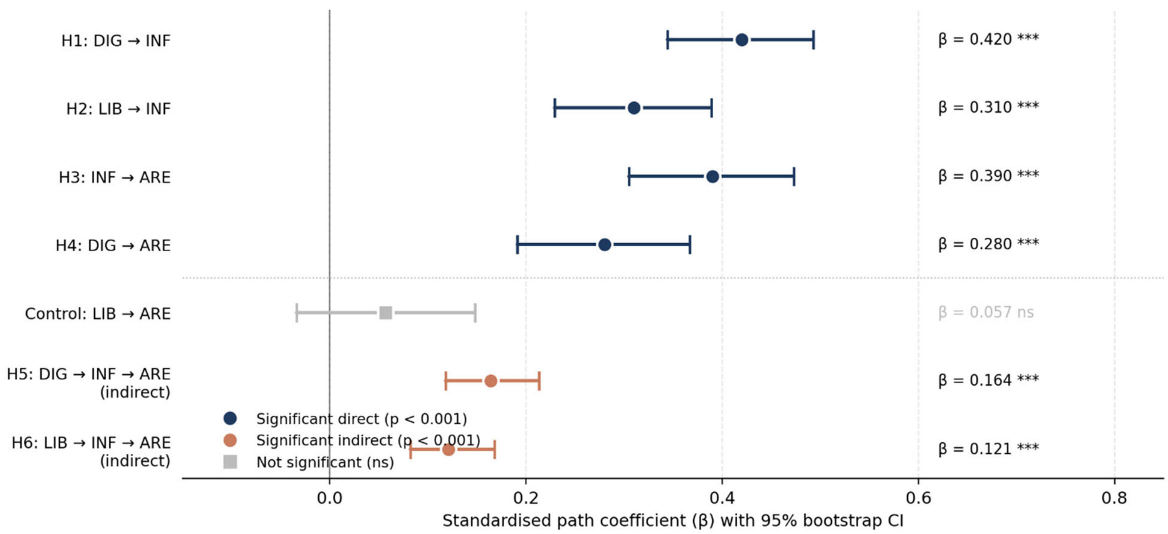
*** $p < 0.001$; ns = not statistically significant. β is standardised; SE from bootstrap with 5,000 resamples; 95% CI percentile (Hair et al., 2022). All four hypothesised paths (H1–H4) are statistically significant (CIs do not contain 0). The control path LIB → ARE was added to provide grounds for classifying the mediation type per Zhao et al. (2010); the result is non-significant (CI contains 0).

All four direct hypotheses (H1-H4) were confirmed. The digital learning environment had the strongest impact on information behaviour (β = 0.420). This was followed by the impact of information behaviour on academic reading (β = 0.390). Library support had a clear positive impact on information behaviour (β = 0.310), but it was weaker than that of the digital learning environment. The direct impact of the digital learning environment on academic reading (β = 0.280) was lower than the impact through information behaviour, which is analysed in Section 4.6. Notably, the additional LIB → ARE direct path was not statistically significant (β = 0.057; t = 1.21; p = 0.225; 95% CI [-0.034; 0.148]) after controlling for the mediating variable INF, suggesting that library support does not directly impact academic reading but only indirectly influences it through information behaviour. The mediating analysis is also given in Section 4.6.

Coefficients of determination were (a) R^2 of INF = 0.381 (moderate); and (b) R^2 of ARE = 0.512 (moderate - strong) according Hair et al., 2022. Stone-Geisser predictive coefficients were (a) Q^2 of INF = 0.201; and (b) Q^2 of ARE = 0.287. As both values exceeded zero, the predictive power of the model was confirmed.

Figure 6

Forest Plot of Standardised Path Coefficients (β) with 95% CIs



Source. Authors' analysis based on PLS-SEM estimation with bootstrap of 5,000 resamples (N = 853). The figure visualises the path coefficients reported in Table 4 (direct paths plus control) and Table 5 (indirect paths).

4.6. Mediation analysis (H5, H6)

The two mediating hypotheses (H5 and H6) were tested using a bootstrap of 5,000 replicates. The 95% confidence intervals of the bias-corrected indirect effects did not contain zeros, confirming that they were statistically significant (Table 5).

Table 5

Mediation Results

Hyp.	Indirect path	Indirect effect (β)	95% CI	VAF (%)	Mediation type
H5	DIG → INF → ARE	0.164***	[0.118; 0.213]	36.9	Complementary partial mediation
H6	LIB → INF → ARE	0.121***	[0.082; 0.168]	n/a (direct path ns)	Indirect-only mediation (full)

*** $p < 0.001$. VAF (Variance Accounted For) = indirect effect / total effect. Mediation classification follows Zhao et al. (2010), based on the statistical significance of two paths: (a) complementary partial mediation both direct and indirect paths are significant and in the same direction; (b) indirect-only mediation (equivalent to the earlier concept of "full mediation"), only the indirect path is significant, while the direct path is not (see Table 4).

Based on the results, H5 is thus confirmed: there exists a complementary partial mediation in the DIG → ARE relationship, both the indirect (β = 0.164) and direct (β = 0.280) pathways are statistically significant and have the same positive direction; VAF = 36.9% means that approximately 37% of the total impact of the digital learning environment on academic reading is transmitted through informational behaviour. The final hypothesis (H6) is also confirmed, but according to Zhao et al.'s (2010) classification, this refers to indirect-only mediation (equivalent to the concept of complete mediation according to previous classifications): the indirect LIB → INF → ARE path is statistically significant (β = 0.121), but the direct LIB → ARE path was tested and is not statistically significant (β = 0.057; 95% CI [-0.034; 0.148] contains the value 0) (see Table 5). Thus, library support influences academic reading primarily through enhancing students' information behaviour, rather than possessing an independent significant direct impact. This is an important finding for policy implications, which is discussed in Section 5.

The summary of hypothesis testing results is thus as follows: all six hypotheses were accepted with a statistical significance $p < 0.001$. The model explains 51.2% of the variance in academic reading engagement and 38.1% of the variance in information behaviour.

4.7. Discussion

4.7.1. Interpretation of Key Findings

The integrated model in this research studies the impact of digital learning resource environment, library support, and information behaviour on academic reading engagement among Vietnamese ODL students. The results support all six hypotheses and shed light on three aspects important to both theory and practice.

The digital learning resource environment is the main factor in information behaviour. The coefficient $\beta_{DIG \rightarrow INF} = 0.420$ is the largest in the model. This indicates that the quality and integration of the LMS, academic databases, and online learning tools most strongly determine how students find, evaluate, and use information. This finding is consistent with Borgman's (2007) academic knowledge infrastructure framework but quantifies the level of impact, something that previous studies, such as Nicholas et al. (2014), only described qualitatively. That 68.5% of students in the HOU sample were found to regularly read online materials is comparable to the 71% finding in Malaysia (Abang Yusof, 2021) and the 73% finding in India

(Subaveerapandiyan & Sinha, 2021). This reflects the specific ODL environment in which digital materials are the primary learning medium.

Indirect-only information-mediated behaviour relates to the library-reading relationship. The direct LIB → ARE path is not significant (β = 0.057; ns) after controlling for the mediating variable, while the indirect LIB → INF → ARE path is significant (β = 0.121; sig). This is the most theoretically important finding: university libraries do not directly impact reading habits; the entire influence is mediated through students' information literacy. This finding refines Borgman's (2007) infrastructure framework at a core point: infrastructure itself does not generate reading activity; absorptive capacity is needed as a bridge. That only 41.2% of students regularly access the library's digital resources is a rate that is significantly lower than the 67% reported by Nicholas et al. (2014). At the same time, this provides quantitative evidence for the last-mile problem and the attitude-behaviour gap that the TPB (Ajzen, 1991) pointed out (i.e., students rated the library very positively (M = 4.12) but did not utilise it accordingly).

Time competition from digital entertainment is a structural factor. The 5.7:1 ratio between digital entertainment time and academic reading time, along with the large difference between high and low social media use (t = 9.21; d = 1.12, which is considered a large effect according to Cohen, 1988), reinforces the media displacement theory (Williams, 1986; Annisette & Lafreniere, 2017). This ratio is higher than regional references: Saaid and Wahab (2014) reported a ratio of 3:1 in Malaysia; Mirza et al. (2021) reported a ratio of 4.2:1 in Pakistan. These findings are possibly due to the high time autonomy demonstrated by distance learning students.

This presents both an opportunity and a challenge, and two theoretical extensions can be drawn from this. First, the displacement is uneven, with final-year students and social science students demonstrating better resistance, which suggests a moderating role of academic demand. Secondly, digital technology not only replaces but also restructures the nature of reading, shifting it from sequential to nonlinear. This fact is consistent with findings by Wolf (2018) and Carr (2010).

A finding requiring caution is the mean reading time of 3.91 hours per week (95% CI [3.79; 4.03]). This figure is lower than both international and regional estimates. Internationally, Mizrachi et al. (2021) reported 8.5–12 hours per week, while regional studies reported 5.2 hours a week in Pakistan (Mirza et al., 2021) and 4.8 hours a week in Indonesia (Tanjung et al., 2017). However, direct comparisons are limited by differences in the definition of academic reading, measurement methods, and sample characteristics between studies; in addition, most reference studies also do not report CI. Nevertheless, the order of magnitude remains a significant indicator.

4.7.2. Contributions

Theoretically, this study extends the media displacement theory by quantifying the degree of mobility in distance higher education in a developing country. This includes refining Borgman's (2007) infrastructure framework through the discovery of indirect-only mediation and simultaneously combining three components—digital environment, library support, and information behaviour—in a single structural testing model, thus allowing for the detection of different mediating roles (partially with DIG, indirectly-only with LIB). This is something that simple regression methods cannot detect. Methodologically, the 22-variable scale has been translated and adapted into Vietnamese, and its reliability and validity have been tested, making it suitable for further research.

The novelty of this study can be articulated in three ways that differentiate it from prior international work. First, existing SEM-based studies on digital technology and reading (e.g., Abang Yusof, 2021; Subaveerapandiyan & Sinha, 2021) treat library support as a background variable or omit it entirely, whereas the present study incorporates it as a full latent construct and reveals its indirect-only mediated pathway. This finding is both empirically new and theoretically consequential. Second, where most Southeast Asian studies (e.g., Saaid & Wahab, 2014; Tanjung et al., 2017) rely on simple bivariate or regression-based analyses, this study employs the PLS-SEM with bootstrapped mediation tests, enabling a richer decomposition of direct and indirect effects. Third, by focusing on an ODL institution that adopts flexible scheduling and predominantly enrols adult learners, this study captures a population systematically underrepresented in international reading research, thereby extending the boundary conditions of the media displacement theory to a context in which time autonomy is greater than in conventional campus settings.

4.7.3. Limitations

Four limitations need to be acknowledged when interpreting the results. First, the convenience sample at a single institution with the specific characteristics of ODL may prevent generalisability to full-time students. The HOU student body is predominantly working adults with families, which may amplify time-competition effects (i.e., lower available leisure time) and reduce library utilisation (due to limited campus access) relative to residential full-time students. Replication in campus-based universities, private institutions, and other Southeast Asian ODL providers is therefore necessary before the findings can be generalised. Alternative explanations for the strong DIG → INF path should also be considered: students who are more academically motivated may both invest more in LMS/database use and engage in more information-seeking behaviour independently of the digital environment, meaning that academic motivation (unmeasured in this study) could act as a confounding third variable. Similarly, the non-significant LIB → ARE path may reflect genuine absence of a direct effect, but it may also reflect restricted variance in library utilisation (i.e., floor effects), low statistical power for this specific path given its relatively small expected effect size, or the fact that the LIB scale captured perceived quality rather than actual usage frequency. Future studies should include behavioural library-use measures alongside the current perceptual scale. Second, the data are entirely self-reported, so there is a risk of bias due to societal expectations, thus, supplementing with objective behavioural data (e.g., access logs, application usage time) will increase reliability. Third, the cross-sectional design does not allow for causal conclusions; longitudinal or experimental studies are necessary. Fourth, the model only measures the digital learning environment and does not include the digital entertainment environment as a latent variable in parallel with the reverse hypothesis; time competition is only analysed descriptively in Section 4.4. Further studies should integrate both digital components in the same PLS-SEM model to directly test the media displacement theory, while also adding psychological factors (e.g., reading motivation, self-regulation capacity) that may explain the variance not explained by the model (≈ 49%).

4.7.4. Practical Implications

To clarify the strength of the evidence, the implications are divided into two groups. Group A is derived directly from the quantitative results, and is described as the following: (A1) information literacy training must go hand in hand with investment in library infrastructure because $\beta\_LIB \rightarrow ARE$ is not directly meaningful (inferred from H6); (A2) the digital learning resource environment is the strongest lever, thus improving quality and integrating LMS/databases should be prioritised (inferred from $\beta\_DIG \rightarrow INF = 0.420$); (A3) barriers to accessing library resources need to be reduced because the twofold difference between library access (41.2%) and Google (82.1%) is evidence of a last-mile problem; and (A4) environmental solutions are needed to reduce time competition between academic reading and digital entertainment, as the ratio of 5.7:1 and $d = 1.12$ indicate this is a structural problem, not an individual will.

Group B proposes additional measures based on international theory and practice that require testing: (a) integrating library materials directly into the LMS and establishing key performance indicators for average reading time (at the institutional level); (b) integrating information literacy training into the main curriculum, single sign-on, and subject-specific reading playlists (at the library level); (c) structured reading exercises with checklists and reflective prompts, along with collaborative reading tools such as Perusall/Hypothesis at the faculty level, based on Wolf (2018); Singer and Alexander (2017); and (d) time-blocking/digital sabbath techniques and prioritising academic databases (at the student level, based on Annisette and Lafreniere, 2017). The effectiveness of Group B's proposals in the specific ODL context in Vietnam requires controlled trials before widespread implementation. Mixing the two types of implications, as many studies often do, risks creating a false sense of evidence strength for each policy proposal.

5. Conclusion

This study constructs and validates a PLS-SEM integrating digital learning environment, library support, information behaviour, and academic reading engagement, based on survey data obtained from 853 HOU respondents. All six hypotheses (four direct and two indirect) were confirmed at $p < 0.001$; the model explains 51.2% of the variance of the dependent variable. The key finding of this study is that information behaviour is partially mediated by the digital learning environment but indirect-only mediated by library support, suggesting two different intervention strategies for the two sources of influence.

Four research directions are proposed. First, the survey should be expanded to include more types of higher education institutions (regular, ODL, public, private) to test generalisability. Second, objective behavioural data from use of LMS, electronic library systems, and mobile devices should be integrated. Third, an intervention experiment should be designed to test the practical effectiveness of the policy implications. Fourth, moderating variables such as learning motivation, self-regulation capacity, and specific academic requirements by discipline should be studied.

Digital technology influences academic reading in a two-way manner: the digital learning environment expands access to knowledge through information behaviour, however, digital entertainment competes for time with academic reading (at a ratio of 5.7:1). The function of university libraries need to be repositioned from resource gateway to facilitator of reading behaviour, with information literacy training as a core component, because results show that libraries only influence academic reading through students' information behaviour (i.e., this is an indirect-only mediation). That HOU students spend only 3.91 hours a week on reading is a finding that is lower than regional references: this requires synchronised intervention at all four levels: university, library, faculty, and students.

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Ethics Statement: This study was conducted in accordance with HOU's ethical standards and was approved by the Ethics Committee for Scientific Research Of Hanoi Open University (approval number: 01/EC-SR). Participation was entirely voluntary, and all respondents provided informed consent before completing the survey. Respondents were informed of the purpose of the study, their right to withdraw at any time, and their right to remain anonymous.

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