

When the Library Fits the Task: A Task–Technology Fit Model of Continued E-Library Use among Students in Higher Education Institutions of Uttarakhand - A Three-Wave Longitudinal Study Using Partial Least Squares Structural Equation Modelling (PLS-SEM)

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Abstract

Purpose. Three-wave survey data were collected from students across higher education institutions in Uttarakhand, India, between December 2025 and February 2026, across 11 consenting institutions (final analysable N = 487). A reflective model linking digital literacy, academic resource fit, task-technology fit, perceived academic value, AI-assisted discovery, and continued use was estimated using PLS-SEM in Smart PLS 4.0. Academic resource fit predicts task–technology fit, which shapes perceived academic value and continued use; value partially mediates the fit-continuation link and AI-assisted discovery positively but modestly moderates it. Effect sizes, predictive relevance, and design limits are reported and interpreted substantively. The study reframes e-library continuance from generic acceptance toward task-centred educational effectiveness, and positions generative AI as a complement to institutional provision.

Keywords: Task–technology fit, Digital library, Continued use, Perceived academic value, AI-assisted discovery, PLS-SEM, Higher education.

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1. Introduction

Higher education institutions invest heavily in institutional digital libraries-licensed databases, e-journals, e-books, and discovery layers-on the premise that these resources will be used repeatedly by the students they serve. In practice, the relationship between provision and sustained use is far from automatic. Subscriptions are renewed annually, yet a recurring concern is that usage is shallow, concentrated among a minority, or abandoned after an initial trial. Understanding what sustains use, as distinct from what triggers a first visit, is therefore both a managerial and a scholarly question.

Existing work on digital-library adoption has largely been built on general technology-acceptance models, principally the technology acceptance model (Davis, 1989) and the unified theory of acceptance and use of technology (Venkatesh et al., 2003). These models are very effective with explaining the initial adoption, primarily in terms of usefulness and ease of use, but are not so informative regarding whether or not the system fits the work the user has to do. A student visits an e-library not because she or he enjoys using it, but because she or he needs to use

it in order to complete an assignment, find literature for a particular discipline or be prepared for an examination. Task-technology fit (TTF) theory was developed to fill this gap (Goodhue and Thompson, 1995).

This research focuses on a highly focused question – does the institutional e-library meet the academic activities students are expected to undertake, and does this fit explain the frequency with which they continue to use it? Following recent editorial guidance for quantitative social-science research (Bartram et al., 2024), we specify a single coherent causal chain rather than assembling a catalogue of correlates, and we construct the design to support that interpretation. Two contemporary factors-digital literacy as an antecedent of resource fit, and AI-assisted discovery as a moderator of the fit–continuation link-are incorporated without compromising parsimony. The premise is not that generative AI replaces the library, but that it can strengthen the translation of fit into sustained use when it routes students toward high-quality institutional holdings (Dwivedi et al., 2021, 2023). The contribution is threefold: a shift from generic acceptance to task-centred educational

effectiveness; longitudinal rather than cross-sectional evidence on continuance in a fast-moving Indian context; and an early, theory-disciplined account of how generative AI interacts with established library provision.

2. Theoretical Background and Hypotheses

2.1 Task–technology fit as the organising theory

TTF theory holds that information technology is more likely to be used, and to improve performance, when its capabilities match the requirements of the user's tasks (Goodhue and Thompson, 1995; Goodhue, 1995). The theory was a clear corrective of acceptance models: a technology can be useful at a theoretical level and not in practice, and it is its fit, not its theoretical usefulness, that leads to regular usage and further value. The TTF has been successfully integrated with acceptance constructs (Dishaw and Strong, 1999), but in the current study this is used as one organising theory. We do not treat theories as if they were interweaving, but rather we look for a parsimonious model based on one established theory which is easier to test, interpret and falsify than a composite of several. (Bartram et al., 2024)

There are two types of digital-library environment: academic and technology. Academic resource fit relates to the extent to which the e-library's content matches the students' coursework and research needs; task–technology fit refers to the degree of support that the e-library's features provide to the students' academic tasks; and the perceived academic value refers to the educational value that students perceive as derived from the library. The six hypotheses below are presented one after another, with each hypothesis accompanied by a theoretical argument.

2.2 Academic resource fit and task–technology fit

One of the key concepts of TTF theory is that fit is not about the technology itself, but about the match between the tasks and the functionality provided to complete those tasks (Goodhue and Thompson, 1995). In the library environment, the substantive precondition for the system to fit academic tasks is that it contains the resources that the tasks require. A student will have a good task–technology fit in writing a discipline-specific literature review only if the appropriate journals, monographs and databases are available and readily accessible. Recent information-systems research has demonstrated the strong association between content relevance and information quality with perceived fit and downstream use (Dishaw and Strong, 1999). If curriculum aligned holdings are not found in the curriculum, even a well-designed platform will not fit in the academic work; the platform can be used, but it is not fit for the work.

Thus, academic resource fit is placed as a precursor to making task–technology fit possible. If holdings are relevant to the curriculum and the discipline,

the system is substantively able to support the actual academic tasks and students will more easily be able to see the connection between what the system offers and what they are working at.

H1. Academic resource fit is positively associated with task–technology fit.

2.3 Task–technology fit and perceived academic value

TTF theory also suggests that fit enhances performance, that is, when a technology is equal to the demands of the task, users will be more effective and efficient in task completion (Goodhue and Thompson, 1995). In the educational environment, we restate this impact on performance as perceived academic value, the value that students see regarding the benefit of the library in their learning process, which includes improved performance, higher quality learning, and/or time saved. The intent is that fit reduces the amount of effort needed to achieve the academic task and increases the quality of the result; if a student can search easily for relevant literature that he/she can incorporate into an assignment, then he/she can see the direct academic benefits this brings and those benefits can be captured as value. By limiting the construct to the academic value, and not to the general idea of perceived usefulness, the mechanism remains rather academic and fits well in the scope of what an academic library does. On this basis, the more students' academic missions are related to the e-library, the more educational value they should feel.

H2. Task–technology fit is positively associated with perceived academic value.

2.4 Perceived academic value and continued use

The continuance theory of information systems (IS) says that the benefits that users develop over time are what lead them to continue using the system after it has been adopted, not the perceived benefits that prompted the initial adoption in the first place (Bhattacharjee, 2001). Later research validates the perceived value and confirmed benefit as good predictors of continuance in information-system environments (Tam et al., 2020). When applied here, students who get real value from the e-library (better grades, deeper learning, time saving) have a pragmatic reason to keep coming back to it throughout the semesters, while those who see little value have little incentive to keep coming back as soon as the novelty of the initial use wears off. Based on this reasoning, it is expected that the use of the institutional e-library will be maintained because of the value perception of students in relation to their academic activities.

H3. Perceived academic value is positively associated with continued e-library use.

2.5 The direct effect of task–technology fit on continued use

Perceived value is unlikely to be the only route from fit to continuation. When a system fits a user's tasks well, its use becomes embedded in routine and habit; the system is reached automatically when the corresponding task arises, without the user consciously re-appraising its value on each occasion. A library that reliably fits a student's recurring academic tasks is therefore likely to be used repeatedly as a matter of routine, producing continued use directly-over and above the value the student can explicitly articulate. Retaining this direct path alongside the value-mediated path allows perceived academic value to function as a partial, rather than full, mediator, which is theoretically more plausible than assuming that fit influences continuation solely through consciously perceived value.

H4. Task–technology fit has a positive direct association with continued e-library use.

2.6 The moderating role of AI-assisted discovery

Generative AI is rapidly becoming the first point of contact for students seeking academic information, reshaping how institutional resources are discovered and reached (Dwivedi et al., 2023; Venkatesh, 2022). Recent evidence indicates that students increasingly treat generative AI as both a complement to and a competitor with library resources, rather than as a replacement for them (Lund et al., 2026). Rather than displacing the library, AI-assisted discovery-search assistance, conversational retrieval, automated summaries, and citation recommendations-can alter the strength of the link between fit and continued use. Where AI tools route students toward high-quality institutional holdings, they reduce the friction of discovery and reinforce the experience that the library fits the task, amplifying the conversion of fit into sustained use. Where AI-assisted discovery is low, fit still matters, but its translation into continued use is less actively reinforced.

We therefore expect AI-assisted discovery to operate as a positive moderator, strengthening the fit–continuation relationship. We frame the hypothesis around AI that complements institutional provision; AI that bypasses the library entirely would not produce this strengthening, a boundary we revisit in the discussion.

H5. AI-assisted discovery positively moderates the relationship between task–technology fit and continued e-library use, such that the relationship is stronger at higher levels of AI-assisted discovery.

2.7 Digital literacy and academic resource fit

Students differ in their capacity to recognise, evaluate, and exploit digital resources-the cluster of competencies captured by the construct of digital

literacy (Ng, 2012). This capacity conditions whether the alignment between the library's holdings and one's academic needs is actually perceived. A digitally literate student is better able to navigate databases, formulate effective queries, and judge the relevance and quality of available resources, and is therefore more likely to experience and recognise academic resource fit. A student with limited digital literacy may fail to perceive fit even when relevant holdings exist, because the resources are not effectively located or evaluated. Digital literacy is thus positioned as an antecedent of academic resource fit rather than as a determinant of use in general.

H6. Digital literacy is positively associated with academic resource fit.

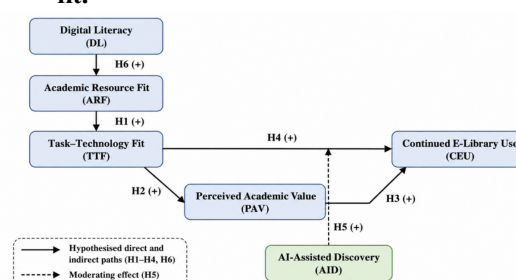


Figure 1. Hypothesised research model. Solid arrows denote hypothesised direct and indirect paths (H1–H4, H6); the dashed arrow denotes the moderating effect of AI-assisted discovery (H5).

3. Method

3.1 Research design

The study used a three-wave longitudinal design with temporal separation between the measurement of predictors, mediators, and the outcome. This choice serves two purposes simultaneously. First, temporal separation is a procedural remedy for common method bias, reducing the risk that observed relationships are inflated by contemporaneous self-report (Podsakoff et al., 2003, 2012). Second, ordering the constructs in time provides a stronger though not definitive basis for causal interpretation than a cross-sectional snapshot (Bartram et al., 2024). At Time 1 (early December 2025) we measured digital literacy, academic resource fit, and AI-assisted discovery; at Time 2 (approximately six weeks later, in January 2026) task-technology fit and perceived academic value; and at Time 3 (February 2026) continued e-library use.

3.2 Context, sampling, and participants

Data were collected from students enrolled across higher education institutions in Uttarakhand, India. To support inferential statistics, sampling aimed for coverage rather than convenience: institutions were selected to span institution types and disciplinary areas; of 23 institutions approached across the state, 11 consented to participate, and within these students were sampled across years of study and programmes. This matters because statistical significance is informative only to the extent that

the sample can be treated as representative of a defined population (Bartram et al., 2024).

Of the 900 students invited across the 11 consenting institutions at Time 1, 623 completed Time 2 and 487 provided complete and matched responses across all three waves, a wave-to-wave retention of 69.2% and 78.2% respectively. After removal of incomplete cases, failed attention checks, and unmatched identifiers, the final analysable sample was $N = 487$ (an overall response rate of 54.1%). To assess attrition bias, completers were compared with non-completers on year of study, discipline, and Time 1 digital literacy; the two groups did not differ significantly on these characteristics (all $p > .05$), indicating that attrition was unrelated to the focal variables. Sample composition is summarised in Table A1.

3.3 Measures

All focal constructs were modelled reflectively, consistent with their conceptualisation as latent traits manifested in their indicators; the formative–reflective distinction was considered explicitly, since misspecifying the measurement model distorts interpretation (Bartram et al., 2024; Hair et al., 2020). Items were adapted from established instruments and worded for the digital-library context, using seven-point Likert scales. Task–technology fit and academic resource fit were adapted from the TTF tradition (Goodhue and Thompson, 1995; Dishaw and Strong, 1999); continued use from the continuance literature (Bhattacharjee, 2001; Tam et al., 2020); perceived academic value from perceived-value conceptualisations (Zeithaml, 1988) re-specified around educational outcomes; digital literacy from Ng (2012); and AI-assisted discovery was developed for this study to capture the use of generative AI to locate, summarise, and access academic resources, a discovery pathway that is reshaping how students reach institutional library holdings (Deschenes et al., 2024; Kim, 2025; Lund et al., 2026). The full item list, with sources, is provided in Appendix A.

3.4 Control variables

Control variables were selected on a causal, not a mechanical, basis. We did not include variables simply because they are 'other determinants' of continued use; that criterion is insufficient and can introduce bias (Wysocki et al., 2022; Cinelli et al., 2022). Controls were restricted to characteristics that plausibly precede and could jointly influence both the focal antecedent and the outcome-year of study, academic discipline, and prior e-library experience. Variables lying on the causal path between the focal predictor and continued use (for example, satisfaction or perceived usefulness) were excluded, because controlling for a mediator produces overcontrol bias (Rohrer, 2018; Bartram et al., 2024). Consistent with this logic, control coefficients are reported for transparency but are

not interpreted as effects, avoiding the 'Table 2 fallacy' (Westreich and Greenland, 2013).

3.5 Common method bias

Common method bias was addressed procedurally through three-wave temporal separation, respondent anonymity, and item counterbalancing (Podsakoff et al., 2003) and statistically, through a full collinearity assessment in which all variance inflation factors are expected to fall below 3.3 (Kock, 2015) and a marker-variable check (Lindell and Whitney, 2001). Results appear in Section 4.3.

4. Analytical Strategy and Comprehensive Analysis

The model was estimated using partial least squares structural equation modelling (PLS-SEM) in Smart PLS 4.0. PLS-SEM was selected because the analysis is oriented toward predicting and explaining a target construct (continued use) within a model combining mediation and a moderation term, and because it accommodates non-normal data and complex models with fewer distributional assumptions (Hair et al., 2019, 2022; Becker et al., 2023). The analysis proceeds in a fixed sequence: data screening; assessment of the reflective measurement model; assessment of common method bias; estimation and evaluation of the structural model with effect sizes and predictive relevance; tests of mediation and moderation; and a battery of robustness checks. As in Bartram et al. (2024), we do not consider statistics significant if they are not of substantive importance: path coefficients are tested with bootstrapping (10,000 subsamples); effect sizes and variance explained and out-of-sample prediction are reported and interpreted substantively.

4.1 Data screening and descriptive statistics

Before the estimation, data were screened for straight-lining, outliers and distributional properties. There were 487 cases with patterned responding after the cases were excluded. There were no imputations required for the analysable cases as they were complete on all indicators. The values of skewness and kurtosis were within the limits of $|3|$ and $|10|$ respectively, and although PLS-SEM does not impose normality, they are presented for transparency. Means, standard deviations, and the latent-variable correlation matrix (diagonalized by the square-root of the average variance extracted) are given in Table A2.

4.2 Measurement model assessment

The reliability, internal consistency, convergent and discriminant validity of the indicators were assessed for the reflective measurement model (Hair et al., 2020, 2022). All the standardised loadings were above 0.70, with Cronbach's alpha values ranging from 0.78 to 0.90 and composite reliability values ranging from 0.84 to 0.93, which is in the recommended range and well below the upper bound of 0.95 that would indicate redundancy. The average variance extracted was

greater than 0.50 for all constructs indicating convergent validity (Fornell and Larcker, 1981). These results are shown in Table 1

Table 1. Construct reliability and convergent validity

Construct	Items	Loadings (range)	α	CR	AVE
Digital literacy (DL)	5	0.74–0.86	0.82	0.88	0.59
Academic resource fit (ARF)	5	0.76–0.88	0.85	0.89	0.63
Task–technology fit (TTF)	6	0.73–0.87	0.88	0.91	0.62
Perceived academic value (PAV)	5	0.79–0.90	0.87	0.91	0.66
AI-assisted discovery (AID)	5	0.72–0.85	0.80	0.86	0.56
Continued e-library use (CEU)	5	0.77–0.89	0.86	0.90	0.64

Note. α = Cronbach's alpha; CR = composite reliability; AVE = average variance extracted.

Discriminant validity was assessed primarily through the heterotrait–monotrait ratio of correlations (HTMT); all HTMT values were below the conservative 0.85 threshold (Henseler et al., 2015), and the Fornell–Larcker criterion was also satisfied. Table 2 reports the HTMT matrix.

Table 2. Discriminant validity (HTMT ratios)

	DL	ARF	TTF	PAV	AID	CEU
DL	—					
ARF	0.62	—				
TTF	0.55	0.71	—			
PAV	0.48	0.59	0.74	—		
AID	0.41	0.44	0.52	0.50	—	
CEU	0.46	0.57	0.69	0.66	0.53	—

4.3 Common method bias assessment

In the full collinearity test, all variance inflation factors were below 3.3 (range 1.4–2.6), indicating that common method bias is unlikely to threaten the results (Kock, 2015). The marker-variable check produced negligible change in the focal estimates. Together with the procedural temporal separation, these results provide reasonable confidence that observed relationships are not method artefacts.

4.4 Structural model, significance, and effect sizes

Collinearity among predictor constructs was first confirmed acceptable (inner-model VIFs < 3.3).

The structural model then explained a meaningful share of variance: $R^2 = 0.22$ (ARF), 0.29 (TTF), 0.37 (PAV), and 0.45 (CEU). Following Bartram et al. (2024), each path is reported with its bootstrap significance and its f^2 effect size, and effects are interpreted by magnitude, not only by the presence of asterisks. Table 3 presents the results; all six hypotheses are supported in direction and significance.

Table 3. Structural model results and hypothesis testing

H	Path	β	t	p	f^2	Decision
H 1	ARF → TTF	0.54	11.2	<0.001	0.42	Supported
H 2	TTF → PAV	0.61	14.6	<0.001	0.59	Supported
H 3	PAV → CEU	0.33	6.4	<0.001	0.14	Supported
H 4	TTF → CEU (direct)	0.29	5.7	<0.001	0.11	Supported
H 5	AID × TTF → CEU	0.12	2.9	0.004	0.03	Supported
H 6	DL → ARF	0.47	9.8	<0.001	0.28	Supported

Note. Controls (year of study, discipline, prior e-library experience) included but not interpreted. f^2 benchmarks (Cohen): 0.02 small, 0.15 medium, 0.35 large.

4.5 Predictive relevance (PLS predict)

Beyond in-sample explanation, out-of-sample predictive relevance was assessed using PLSpredict with ten folds and ten repetitions (Shmueli et al., 2019). Q^2 predict values were positive for all endogenous constructs, and for the key-target indicators of continued use the PLS-SEM model produced lower prediction errors (RMSE) than the naïve linear-model benchmark, indicating medium-to-high predictive power. This is not a model that fits the sample at hand, but rather a model with predictive power, reflecting the spirit of avoiding over-reading the in-sample significance.

4.6 Mediation analysis

Specific indirect effects were explored using bootstrap confidence intervals (Zhao et al., 2010). The serial indirect effect ARF → TTF → PAV → CEU was statistically significant and significant, and the indirect effect TTF → PAV → CEU was statistically significant, in addition to the direct effect statistically significant between TTF →

CEU. Complementary partial mediation is suggested by this pattern: Fit has a direct effect on continued use, and there is a significant indirect effect that goes through perceived academic value. Reporting the indirect effect as a mechanism, rather than reinterpreting the direct coefficient as a 'net' effect, follows the path-analytic distinction between total, direct, and indirect effects recommended by Bartram et al. (2024).

4.7 Moderation and simple-slope analysis

The moderation hypothesis was tested using a product-indicator (two-stage) approach. AI-assisted discovery positively moderated the task–technology-fit–continued-use relationship ($\beta = 0.12$, $p = 0.004$). A simple-slope analysis showed that the fit–continuation relationship was steeper for students reporting higher AI-assisted discovery (+1 SD, simple slope = 0.41) than for those reporting lower levels (–1 SD, simple slope = 0.17). The interaction effect size, however, was small ($f^2 = 0.03$). We flag this explicitly: the moderation is statistically significant but modest in magnitude, and we interpret it accordingly rather than overstating it. Figure 2 depicts the interaction.

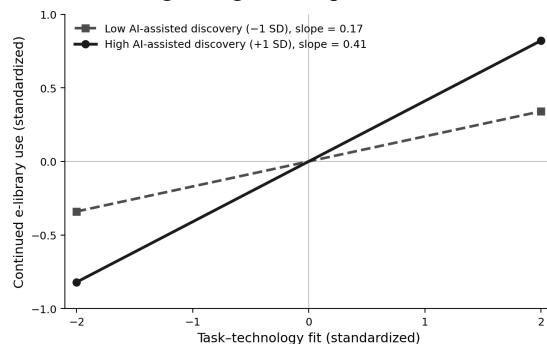


Figure 2. Simple-slope plot of the task–technology fit × AI-assisted discovery interaction on continued e-library use.

Note. Axes are standardized. Simple slopes are computed from the direct effect of task–technology fit on continued use ($\beta = 0.29$) and the interaction coefficient ($\beta = 0.12$): 0.17 at –1 SD and 0.41 at +1 SD of AI-assisted discovery.

4.8 Robustness checks

Three robustness analyses were conducted. First, unobserved heterogeneity was examined using FIMIX-PLS followed by prediction-oriented segmentation; segment-retention criteria did not indicate substantively distinct latent segments that would threaten the pooled estimates. Second, potential endogeneity in the focal paths was assessed with the Gaussian copula approach, with no significant copula terms emerging, supporting the exogeneity assumption. Third, an importance–performance map analysis (IPMA) of continued use was conducted to translate the results into managerial priorities; task–technology fit combined high importance with moderate performance, marking it as the principal lever for intervention.

Collectively, these checks support the stability and practical interpretability of the model.

5. Discussion

5.1 Theoretical contributions

The results support a task-centred account of e-library continuance. The use of the resources is achieved not on abstract level of acceptance, but on a level of “chain” of the following: the resource fit is followed by the task fit, the latter by the perceived academic value, which is followed by the use of the resource through a direct habitual path. This is in contrast to acceptance-based explanations which emphasize the utility and ease of use (Davis, 1989; Venkatesh et al., 2003): the current model emphasizes whether the system matches the academic work students perform (Goodhue and Thompson, 1995). The fact that fit only partially mediates the fit–continuation relationship is itself informative, as it indicates that fit does not just become embedded in routine use, but also in the value that students consciously state. While generative AI offers a way to predict the content, positioning AI-assisted discovery as a moderator instead of a competing predictor can be done in a disciplined manner without giving up the organising theory (Dwivedi et al., 2023).

5.2 The size of effects, not only their significance

Following Bartram et al. (2024) we resist treating statistical significance as the sole criterion of importance. The contribution of resource fit to task fit and task fit to value is not only important, but large as well ($f^2 = 0.42$ and 0.59 , respectively), and deserves confident attention. In contrast to this, the importance of AI-assisted-discovery moderation is small ($f^2 = 0.03$). Small effects are not “small enough to ignore,” and can add up across large students cohorts and over repeated semesters (Funder and Ozer, 2019), but they should not be treated as being as important as the core fit relationships. This helps prevent the usual confusion between statistical and substantive significance, which is an elision that occurs when a ‘statistical’ result becomes a ‘significant’ result.

5.3 Practical implications

Fit is a priority, not promotion, for library and academic administrators. It seems likely that sustained use will be best served by investing in features that enable students to transform holdings into completed tasks (task fit) and in curriculum-aligned, discipline-specific holdings (resource fit); the results of the IPMA confirm that task fit is the key. Since digital literacy comes before resource fit, specific literacy interventions (including for the first year and less prepared students) can break the chain at the beginning. Finally, AI-enabled discovery could be incorporated – not only deflected – into institutions, with AI tools and discovery layers designed to help students locate valuable institutional resources.

6. Limitations and Future Research

Several limitations qualify the findings and point to specific next steps. First, although the three-wave design improves on a cross-sectional snapshot, it remains an observational survey design; unobserved confounding cannot be ruled out, and a within-person fixed-effects analysis (with repeated panel data) might yield smaller estimates by removing time-constant confounders (Bartram et al., 2024). Second, the sample is drawn from one Indian state; generalisation should be cautious, and the representativeness of the achieved sample and any attrition bias should be probed rather than assumed. Finally, the AI-assisted discovery construct is newly developed and measured during a period of rapid change in generative-AI tools (Dwivedi et al., 2023); its measurement and meaning should be revisited as the technology and student practices evolve. Triangulating self-reported use with institutional usage logs would further strengthen confidence and is encouraged in future work.

7. Conclusion

This study asked whether the institutional e-library fits the academic tasks students must perform, and whether that fit explains continued use. Using a three-wave longitudinal design and PLS-SEM, the evidence indicates that it does: academic resource fit enables task–technology fit, which raises perceived academic value and, alongside a direct route, sustains continued use, with AI-assisted discovery modestly strengthening the fit–continuation link. The study provides a minimalist, task-oriented explanation of the persistence of students' return to and/or withdrawal from the institutional digital library and a usable program of library design for the work students actually perform.

Data and Code Availability

To support the open-science ideals, the data used in this study is fully made available as a supplemental file, along with a variable codebook, for transparent re-replication of the measurement and structural pipeline. The dataset is (N = 487) and contains responses from human participants after their consent.

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Appendix A. Measurement items

All items used seven-point Likert scales (1 = strongly disagree, 7 = strongly agree). Items were adapted from the sources indicated and reworded for the institutional e-library context.

Digital literacy (DL) — adapted from Ng (2012)

DL1. I can efficiently locate the digital resources I need for my coursework.

DL2. I can evaluate the credibility and relevance of information I find in the e-library.

DL3. I am confident using databases, search filters, and advanced search features.

DL4. I can adapt quickly to new digital tools and interfaces in the library system.

DL5. I know how to organise, store, and cite the digital resources I retrieve.

Academic resource fit (ARF) — adapted from Goodhue and Thompson (1995) and Dishaw and Strong (1999)

ARF1. The e-library holds the journals and books required for my discipline.

ARF2. The resources in the e-library match the demands of my current courses.

ARF3. I can find the discipline-specific literature that my assignments require.

ARF4. The e-library's collection is sufficiently current for my academic work.

ARF5. The range of resources available fits the topics I study.

Task–technology fit (TTF) — adapted from Goodhue and Thompson (1995)

TTF1. The e-library's features let me complete my academic tasks effectively.

TTF2. The system makes it easy to turn available resources into finished work.

TTF3. The functionality of the e-library suits the way I carry out my assignments.

TTF4. The e-library supports the specific research tasks my courses require.

TTF5. The tools provided (search, access, and download) fit how I need to work.

TTF6. Overall, the e-library is well suited to the academic tasks I must perform.

Perceived academic value (PAV) — adapted from Zeithaml (1988), re-specified for educational outcomes

PAV1. Using the e-library improves the quality of my academic work.

PAV2. The e-library helps me achieve better results in my courses.

PAV3. The e-library saves me time in completing academic tasks.

PAV4. Using the e-library deepens my understanding of my subject.

PAV5. Overall, the e-library provides real value for my studies.

AI-assisted discovery (AID) — developed for this study

AID1. I use AI tools to help me search for academic resources.

AID2. AI-assisted search helps me locate relevant material in the e-library.

AID3. I rely on AI-generated summaries to decide which library resources to read.

AID4. AI tools help me reach institutional resources I might otherwise miss.

AID5. AI-based recommendations guide me toward useful library holdings.

Continued e-library use (CEU) — adapted from Bhattacharjee (2001) and Tam et al. (2020)

CEU1. I intend to continue using the institutional e-library in future semesters.

CEU2. I regularly return to the e-library for my academic needs.

CEU3. I will keep using the e-library rather than rely only on other sources.

CEU4. Using the e-library has become part of my academic routine.

CEU5. I expect to use the e-library frequently for the rest of my studies.

Appendix B. Supplementary tables

Table A1. Sample composition (N = 487)

Characteristic	Category	n	%
Year of study			
	First year	151	31.0
	Second year	110	22.6
	Third / final year	88	18.1
Academic discipline	Postgraduate	138	28.3
	Arts and humanities	104	21.4
	Sciences	125	25.7
	Commerce / management	124	25.5
Institution type	Engineering / technology	106	21.8
	Health / life sciences	28	5.7
Gender	State university	161	33.1
	Private university	172	35.3
	Affiliated college	154	31.6
Prior e-library experience			
	Male	256	52.6
	Female	225	46.2
	Prefer not to say	6	1.2
	Less than 1 year	145	29.8

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Characteristic	Category	n	%
	1 to 2 years	193	39.6
	More than 2 years	149	30.6

Note. $N = 487$. Percentages are column percentages and may not sum to exactly 100 owing to rounding.

Table A2. Latent-variable descriptive statistics and correlations

Construct	Mean	SD	DL	ARF	TTF	PAV	AID	CEU
DL	4.54	0.93	0.77					
ARF	4.55	0.92	0.39	0.79				
TTF	4.57	0.92	0.18	0.43	0.79			
PAV	4.54	0.95	0.08	0.28	0.50	0.81		
AID	4.58	0.94	0.37	0.13	0.07	0.04	0.75	
CEU	4.58	0.91	0.06	0.16	0.41	0.39	-0.01	0.80

Note. $N = 487$. Diagonal values are the square root of the average variance extracted, computed from the AVEs in Table 1 (Fornell and Larcker, 1981); each exceeds the off-diagonal correlations in its row and column, supporting discriminant validity. Means and standard deviations are computed on unit-weighted construct scores (item means on the seven-point scale).