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Economics of Digital Learning and Artificial Intelligence in Higher Education: Impact on Library Use and Student Achievement in Urban Nepal

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Abstract

This study examines the economic relationship between traditional academic resources and digital learning tools, including generative artificial intelligence (AI), among higher education students in Kathmandu, Nepal. Using cross-sectional data from 439 urban students and an ordered logistic regression framework, the study tests substitution and complementarity effects. Results show that e-learning platforms significantly substitute for physical library visits, reflecting reduced transaction costs, while also enhancing academic performance and research participation. In contrast, generative AI use shows no significant association with library demand or academic outcomes, indicating an early stage of adoption. Core library services continue to deliver distinct benefits and cannot be fully replaced by AI or digital tools. The findings support an integrated policy approach that combines strategic investment in library infrastructure and staff quality with the promotion of high-impact e-learning platforms and ethical AI tools to strengthen academic achievement, research engagement, and human capital development.

Keywords: Artificial Intelligence, digital adoption, digital divide, digital learning, digital literacy

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Introduction

The rapid diffusion of digital technologies has fundamentally altered the production, dissemination, and consumption of knowledge in higher education (Hashim et al., 2022). Academic libraries have long been central to higher-education knowledge production, providing curated collections, study space, and mediated access to scholarly resources (Odonnell & Anderson, 2022). However, the last two decades have witnessed a profound reduction in the information search costs and access barriers to knowledge, driven by technological advancements (Adedoyin & Soykan, 2023). The proliferation of digital platforms such as Coursera and Khan Academy, alongside the recent surge of advanced AI-driven tools like ChatGPT and Gemini AI, has fundamentally disrupted the traditional educational production function (Imran et al., 2024). The COVID-19 pandemic accelerated this shift by forcing a large-scale, immediate migration to remote and digitally mediated learning, embedding digital tools more deeply into everyday pedagogy (Adedoyin & Soykan, 2023; Cranfield et al., 2021).

Globally, empirical studies on higher education institutions revealed a sharp rise in the adoption of AI-assisted tools, e-learning platforms, and learning management systems (Rahiman & Kodikal, 2024; Abulail et al., 2025). In addition, digital repositories, personalized learning platforms, and massively open online courses (MOOCs) have increased access to educational materials outside of institutional boundaries (Dwivedi et al., 2023). Generative AI tools have introduced different modes of academic engagement, such as generating summaries, explanations, and problem-solving guidance in real time, and evidence from developed countries highlights that these tools have improved conceptual understanding, learned efficiency, and supported self-regulated learning when used wisely (Dwivedi et al., 2023; Kasneci et al., 2023). This global digital transformation presents unique challenges to low-income countries due to persistent public-finance and infrastructure constraints. Nepal has seen remarkable improvements in digital connectivity over the last decade (Pandey & Regmi, 2018). National internet penetration has reached approximately 90%, and smartphone ownership exists in 76% of households (Oli, 2023). Government policies aimed at digital literacy and the availability of cheaper mobile data have lowered the barriers to entry for internet-based learning. Consequently, for many urban students, digital platforms offer flexible, personalized, and near-instantaneous alternatives to traditional methods of information retrieval.

On the other hand, the "supply side" of traditional academic resources in Nepal remains critical due to chronic public underinvestment (Dahal & Baral, 2024). Despite a significant expansion in the number of schools and universities, the accompanying physical infrastructure has lagged considerably. Nepal's national education budget hovers around approximately 15% of total expenditure, a figure heavily dominated by recurrent costs such as salaries, leaving minimal fiscal space for capital expenditures like library construction, book acquisition, or technological upgrading within institutions (Joshi, 2023). The government's ambitious "One School One Library" program has largely stalled due to these budgetary realities. Consequently, a significant portion of educational institutions lack functional libraries

entirely. Existing libraries, including Tribhuvan University Central Library, often suffer from outdated collections, physical damage from the 2015 earthquake that has yet to be repaired, and acute shortages of trained human resources (Singh & Nyaichyai, 2023; Pal, 2021).

Furthermore, a significant digital divide persists; while urban centers adopt new tech, rural areas still struggle with basic electricity and internet infrastructure, making them doubly disadvantaged (Niraula, 2023). This divergence creates a critical resource allocation dilemma at the heart of Nepal's higher education policy. Students, acting as rational agents seeking to maximize their educational utility subject to constraints, are increasingly faced with a choice between under-resourced physical libraries and increasingly powerful, accessible digital alternatives (Nongalo, 2025). This duality, growing digital access alongside weak physical infrastructure, creates a policy-relevant question about resource allocation in higher education: do modern digital tools function as substitutes for traditional libraries, or do they operate as complements that depend on a baseline of library-based skills and resources?

Although the prior studies have examined AI-based learning, e-learning platforms, technology adoption, digital information-seeking behavior, and pedagogical implications of AI tools (Pasupuleti et al., 2025; Fu et al., 2024; Pham et al., 2024), few studies have explored the joint effects of generative AI, online learning platforms, and traditional library use within a developing country context (Adarkwah et al., 2024; Meakin, 2024). Evidence from Nepal remains especially limited. Most existing studies focus either on general technology adoption or on the perceived usefulness of generative AI tools, but there are limited studies focusing on whether digital technologies are displacing library usage or supplementing it, or changing the nature of the library.

Consequently, evidence is limited on whether digital technologies are displacing library usage, supplementing it, or changing the nature of library–student interactions in ways that matter for academic success. This study addresses this empirical gap by examining how e-learning platforms and AI-assisted tools are influencing traditional library utilization and academic outcomes among the urban higher-education students in Nepal. Based on the Technology Acceptance Model (TAM) and the diffusion of innovation theory, this study frames the student preferences and choices as a resource-constrained utility maximization. The adoption decisions reflect perceived usefulness, ease of use, and access to infrastructure, while library visitation captures an alternative (or complementary) means of securing academic inputs. Using ordered logistic regression on survey data, this study examines the relationship between the adoption intensity of modern digital tools (generative AI use) and the frequency of traditional library usage, and links these patterns to measure the academic performance of university students.

This research contributes to the literature in several distinct ways. First, it provides empirical evidence on the combined effects of generative AI and e-learning platforms within a low-income, developing country context, an area currently under-researched. Second, it quantifies whether digital learning tools are acting as efficient substitutes for, or complements to, institutional libraries, a distinction with direct implications for where scarce public and

institutional funds should be invested. Finally, by connecting adoption behavior with academic outcomes, the study provides evidence for policymakers and university administrators on how to integrate both traditional and digital resources to maximize student success.

Literature Review

Theoretical Underpinning

To comprehend the adoption and intensity of use of digital and AI-assisted educational tools, as well as their impact on traditional libraries, it is essential to draw on multiple theoretical perspectives, including technology acceptance, resource allocation, and individual decision-making theories.

TAM (Davis, 1989) provides a foundation explanation for individual adoption behavior. The model centers on perceived usefulness and perceived ease of use as the primary determinants of technology acceptance. In the context of higher education, students may engage with digital platforms such as generative AI tools, e-learning modules, and adaptive learning systems, which are more efficient and convenient than navigating physical libraries (Dumitru, 2024). These tools provide quick access to updated information and personalized learning experiences, reducing the time and effort required to obtain academic materials. Hence, TAM captures attitudinal and micro-level cognitive explicitly influence the intensity of AI adoption.

Likewise, Diffusion of Innovation Theory (DOI) by Rogers et al. (2014) emphasizes adoption heterogeneity based on compatibility, relative advantage, observability, and trialability of the innovation. In Nepal, there is a disparity of internet access, institutional support, digital divide, disparities in digital literacy, and social influence, which creates variation in intensity and likelihood of AI adoption (Chand et al., 2024). It is also relevant to Nepal's urban higher education sector, where students in private and technologically advanced institutions often serve as early adopters of AI-driven learning tools. Thus, DOI reinforces that adoption should be modeled as an order process rather than a binary event, emphasizing the gradations from early to late adopters and non-users.

Venkatesh et al. (2003) expanded earlier models by proposing the Unified Theory of Acceptance and Use of Technology (UTAUT), which identifies four determinants of technology adoption: performance expectancy, effort expectancy, social influence, and facilitating conditions. This model suggests that students' preference for tools such as ChatGPT or internet-based learning platforms depends not only on perceived usefulness but also on institutional support, peer influence, and the availability of digital infrastructure.

The student learning choice can be emphasized from the perspectives of a resource-constrained utility maximization problem. According to this viewpoint, students disseminate their resources, such as time, cognitive effort, and access costs, into various academic inputs, such as traditional library visits and digital tools (Kato et al., 2021). Both the AI-enabled platform

and library can work as complementary or substitutable inputs (Okunlaya et al., 2022). Therefore, choosing to use one or both resources is an example of optimization behavior that maximizes projected academic success under limitations.

Furthermore, the educational production function model emphasizes academic performance as the output developed holistically from the integration of learning inputs (Glewwe et al., 2020). The availability may not only impact the student outcomes but also the way in which inputs are integrated and utilized. Library usage may support the critical analysis, structured knowledge acquisition, and support the depth of the knowledge, whereas the AI adoption may enhance the efficiency and productivity by fostering the learning effectiveness and information availability (Okunlaya et al., 2022). Hence, the overall academic performance explicitly depends upon how the various inputs complement or replace one another, as mediated by the student choices and resource limitations.

Empirical Review

A growing number of empirical studies explore the relationship between AI-driven tools, online learning platforms, and traditional learning environments. Aldawsari and Almohish (2024), studying educational technologists in Saudi Arabian universities, found support for integrating digital learning tools into online higher education where whereas Mese et al. (2024) revealed that combining ChatGPT with structured e-learning improved radiology education. These findings suggest that while students increasingly use AI tools, such adoption does not necessarily eliminate the relevance of traditional learning platforms.

Other studies highlight how digital tools may influence student behavior. Stanoyevitch (2024), examining exam scores before and after ChatGPT's introduction, reported higher rates of academic misconduct and a growing preference for online classes. This preference suggests a potential decline in students' physical presence in classrooms and libraries.

Research by Kanbul and Mohammed (2024), based on 2,936 datasets, indicated that ChatGPT use enhances student motivation, self-confidence, and independent learning. Similarly, Gill et al. (2024) observed that AI-driven tools encourage self-directed learning. Taken together, these findings imply that increased AI use may enhance academic achievement, foster problem-solving skills, and improve study efficiency that relying solely on traditional learning methods.

At the same time, several studies note that library engagement remains influenced by institutional and behavioral factors. Azhari and Ramadan (2022) reported that although student reading interest was low, many still visited school libraries two to four times per week for reading, discussion, or leisure. Conversely, social media strategies appear ineffective in drawing students to physical libraries. Studies from the University of Hong Kong Libraries by Cheng et al. (2020) and Lam et al. (2022) found that Facebook and Instagram marketing did not significantly increase library visits.

The COVID-19 pandemic further accelerated the shift toward digital learning. Connell et al. (2021), analyzing data from several U.S. universities, found that physical library visits declined sharply, with students increasingly relying on virtual communication. Zhou (2022) similarly showed that students in China and Italy preferred to continue distance learning even after pandemic restrictions were lifted.

As traditional libraries evolve, e-libraries have emerged as a promising alternative. Rahmat et al. (2022) found that medical students in Pakistan had a positive experience using e-library services, which supported continuity in their studies. Burns et al. (2020) reported that dental students widely used YouTube for clinical learning, though concerns about reliability remained. Increasing reliance on video-based learning suggests a gradual shift away from library-based academic resources.

Other studies highlight mixed attitudes toward digital resources. Casselden and Pears (2020) noted that students at British universities appreciated the efficiency of eBooks but faced challenges related to platform complexity and restrictive licensing. Arman (2020) found that students often avoided library visits due to easy access to information via smartphones and a reliance on instructor-provided handouts.

Recent studies have focused on how traditional library utilization and digital technology interact with each other (Prajapat et al., 2022; Rafi et al., 2019). Findings have demonstrated that digital platforms may work as a supplement mechanism rather than replacing the physical libraries, demonstrating that with digital access, students will be able to access information more efficiently while retaining the library for structured study and in-depth and critical learning. In contrast, few Rosman et al. (2019) and Sharma and Khan (2024), have indicated that digitally embedded tools can work as a substitution effect, as the regular use of digital resources may diminish the visits to libraries, which can significantly impact the depth and breadth of academic engagement.

This demonstrates that digital learning platform significantly impacts the holistic engagement of students and academic performance, the relationship between AI-embedded tools and traditional library usage is context-dependent and can both work as a complementary or substitutive mechanism, and the intensity and adoption of AI-embedded learning tools vary significantly according to technological, individual, and infrastructural factors.

Context of Nepal

Nepal's higher education has gone through significant growth over the past several decades (Paudasiani, 2025), and the incorporation of major digital infrastructure in major cities. Despite these advancements, the usage and adoption of digital learning platforms remain uneven. Colleges in urban cities like Kathmandu, Pokhara, Biratnagar, and other metropolitan areas are integrating digital learning solutions to support the traditional curriculum (Baral, 2025), but this co-exists with the presence of the traditional library-based learning, creating two approaches for knowledge acquisition. Still today in Nepalese universities, the traditional libraries play a key role in providing vital academic resources, reference materials, and a study

environment, given the limited access to the global databases for many students (Subedi, 2025). But the preliminary evidence suggests that digital learning tools, e-learning modules, and online repositories are starting to drive student behaviors and reduce their visit to the physical library.

Subedi et al. (2020) noted that although e-learning provides valuable continuity during crises, its effectiveness is limited by weak digital infrastructure, inadequate training, and unequal access. Acharya and Bansyat (2024) found that teachers in the Kirtipur region viewed ChatGPT as a useful tool for enhancing classroom instruction, particularly for personalized learning. Similarly, Lawaju et al. (2024) observed that perceived usefulness, ease of use, and user attitudes strongly influenced ChatGPT adoption among students in Kathmandu-based management programs. However, concerns about data privacy, reliability, and accuracy persist, making traditional libraries an important complementary resource for credible information.

Yadav and Pokhrel (2023) found that joy and perceived usefulness strongly shaped ChatGPT use among Nepalese users, which may gradually reduce reliance on physical libraries. Ghimire et al. (2024) provided further insight into higher education, noting that although students appreciated the convenience of ChatGPT, many acknowledged becoming less motivated to engage in library-based research. Dahal (2024) raised concerns about overreliance on generative AI in qualitative research, highlighting risks to academic integrity and traditional research practices, including library-based literature review.

Research Methods

This study employs a cross-sectional research design, with a focus on quantitative methods. The study population consists of the undergraduate and graduate students enrolled in various private and public higher education institutions in Kathmandu Valley (i.e., Kathmandu, Bhaktapur, and Lalitpur districts), who have access to both digital learning platforms and traditional library resources.

Following Cochran's (1997) sample size formula for an infinite and large population, the minimum sample size was estimated to be 385 responses (using a 95% confidence level and a 5% margin of error). The study was based on simple random sampling, and the data were collected using a structured survey questionnaire. Among the 500 distributed questionnaires, 439 usable responses were finalized for further analysis after eliminating the outliers, missing values, and incomplete forms. Both offline and online mode via the Kobo Toolbox was used to administer the survey questionnaire. online and offline were administered.

The study employed simple random sampling as our sampling method to ensure an unbiased representation of the target population. Data were collected through a structured survey using both online and offline modes, facilitated by the Kobo Toolbox application. The survey was conducted among students enrolled in higher education institutions in Kathmandu, covering both public and private colleges and universities. Data was collected between October to December 2024. Similarly, the operational description of variables is presented in see annex Table A1.

Econometric Model

Since the dependent variable is categorical with more than two outcomes and possesses a natural ranking, the study used an ordered logistic regression model. In our previous study, Sagar et al. (2024), an econometric model was formulated for an ordered logistic regression, in which the cumulative probability of being at or below category j, given the vector of explanatory variables Xi, is specified as:

$$P(Y \leq j \mid \mathrm{X}) = \frac{1}{1+\exp(\beta \mathrm{Xi} - \mathrm{Kj})}$$

Where, is the vector of coefficients for the explanatory variables Xi

Kj is the threshold parameter associated with each category *j* and *j* = 1, 2, 3, 4, and 5

To derive the probability for each category $Y = j$, the cumulative probabilities of adjacent categories were subtracted:

$$\mathrm{P(Y = j \mid X)} = P(Y \leq j \mid \mathrm{X}) - P(Y \leq j - 1 \mid \mathrm{X})$$

For a dependent variable with 5 categories (*j* = 1, 2, 3, 4, and 5), the individual probabilities are mathematically expressed as follows:

Category 1:

$$\mathrm{P(Y = 1 \mid X)} = \frac{1}{1+\exp(\beta \mathrm{Xi} - \kappa 1)}$$

Note: Replace P(Y=2,3,4,5 | X) for Category 2,3,4,5, respectively.

For the empirical analysis, the original ordered regression model can be formulated as:

Model-1

$$FTLV = \alpha + \beta 1AGE + \beta 2\ GEN + \beta 3ATC + \beta 4EIP + \beta 5TLI + \beta 6LB + \beta 7BPB + \beta 8ULS + \beta 9DRTL + \beta 10ADRTL + \beta 11APE + \beta 12ASF + \beta 13PRP + \beta 14ADR + \beta 15PE + \beta 16CP + \mu$$

Model-2

$$APE = \alpha + \beta 1AGE + \beta 2\ GEN + \beta 3ATC + \beta 4EIP + \beta 5TLI + \beta 6LB + \beta 7BPB + \beta 8ULS + \beta 9DRTL + \beta 10ADRTL + \beta 11FTLV + \beta 12ASF + \beta 13PRP + \mu$$

Model-3

$$PRP = \alpha + \beta 1AGE + \beta 2\ GEN + \beta 3ATC + \beta 4EIP + \beta 5TLI + \beta 6LB + \beta 7BRB + \beta 8ULS + \beta 9DRTL + \beta 10ADRTL + \beta 11FTLV + \beta 12ASF + \beta 13APE + \mu$$

Model-4

$$ATC = \alpha + \beta 1AGE + \beta 2\ GEN + \beta 3EIP + \beta 4TLI + \beta 5LB + \beta 6BRB + \beta 7ULS + \beta 8DRTL + \beta 9ADRTL + \beta 10FTLV + \beta 11ASF + \beta 12PRP + \beta 13APE + \mu$$

Where μ is the error term.

The separate ordered logistic regression models have been formulated for each dependent variable. It includes the frequency of traditional library visits (FTLV), academic performance of students (APE), participation in research and writing (PRP), and average time spent on ChatGPT (ATC). Similarly, other important variables of the model have been systematically presented in Table 1.

Result and Analysis

Demographic Information of Respondents

The data reveals that a majority of respondents are aged between 22 and 26 years (64.92%), with the average age being 25 years. Gender distribution is nearly balanced, with 46.45% male and 53.55% female participants. Most respondents hold a Master's degree (54.21%) and are primarily from the disciplines of Management (34.62%) and Science (25.28%), with the lowest representation from Education (18%). Additionally, a significant majority (77.17%) are studying in public higher education institutions.

Model's Robustness Check

An ordered logistic regression model has certain pre-assumptions to be satisfied. The mean-variance inflation factor (VIF) is 1.29, indicating no presence of severe multicollinearity in the model. Similarly, the Breusch–Pagan/Cook–Weisberg test was employed for assessing the presence of heteroskedasticity, and the findings revealed no significant evidence of heteroskedasticity in both models. These two diagnostic tests ensure the robustness of the model. Although Pseudo R-Squared does not make much sense in an ordered logit regression, it still provides a tentative goodness of fit of the model. The Pseudo R-Squared is above 20% in all models, which represents moderate goodness of fit in cross-sectional data.

Correlation Analysis

Table 1 presents the pairwise correlation coefficients for the key variables in the dataset, which provides essential preliminary insights into the structural relationships between student behaviors and resource utilization.

First, the findings revealed a statistically significant positive correlation between the frequency of traditional library visits and indicators of human capital accumulation. Specifically, library usage is positively associated with academic performance in exams and assignment submission frequency. Furthermore, the positive correlations with peer collaboration and the perceived effectiveness of the library were established. These results suggest that students who utilize the library as a physical club good are also those exhibiting higher levels of academic discipline and social capital.

Counter-intuitively, supply-side factors, specifically traditional library infrastructure and access to digital resources within the library, do not exhibit statistically significant correlations with usage frequency. Regarding the adoption of new technologies, the results reveal a divergence between different types of digital tools. Librarian behavior and the time allocated to AI tools show no significant correlation with traditional library usage. In contrast, the intensity of engagement with e-learning platforms displays a statistically significant negative correlation with traditional library usage. This provides preliminary evidence of a substitution effect: as students shift their time allocation toward accessible, multimedia-rich digital platforms, the marginal utility of visiting a physical library appears to diminish.

Table 1

Pairwise Correlation Between Variables

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(1) FTLV	1.00								
(2) TLI	.09	1.00							
(3) LB	.00	.00	1.00						
(4) ADRTL	.08	.17*	.17*	1.00					
(5) APE	.12*	.00	.09	.12*	1.00				
(6) ASF	.20*	.00	.12*	.15*	.25*	1.00			
(7) ATC	.00	.00	.00	.00	.00	.00	1.00		
(8) CP	.12*	.11*	.00	.00	.11*	.00	.12*	1.00	
(9) EIP	-.14*	.00	.00	-.16*	.26*	.13*	.00	.15*	1.00

Note (s). *** p<.01, ** p<.05, * p<.1; Abbrebrations are described in Table A1 in the Annex; Field Survey (2024)

Regression Analysis: Model-1

Table 2

Effect of Average Time Spent on ChatGPT and AI Tools, and E-Learning Platforms, on the Frequency of Traditional Library Usage

FTLV	Coef.	Log Odd	Marginal Effect				
			Pr(O=1)	Pr(O=2)	Pr(O=3)	Pr(O=4)	Pr(O =5)
GEN	.44**	1.56**	-.02**	-.04**	-.01**	.04**	.03**
	(.19)	(.30)	(.00)	(.01)	(.00)	(.01)	(.01)
EIP	-.03**	1.26**	.01**	.02**	.01**	-.01**	-.02**
	(.08)	(.09)	(.00)	(.00)	(.00)	(.00)	(.00)
TLI	.26**	1.3**	-.01**	-.02**	-.01**	.02**	.02**
	(.13)	(.17)	(.00)	(.01)	(.00)	(.01)	(.01)
LB	-.23*	.78*	.01*	.02*	.00*	-.02*	-.01*
	(.13)	(.10)	(.00)	(.01)	(.00)	(.01)	(.01)
BPB	.62***	1.87***	-.02***	-.05***	-.02***	.06***	.04***
	(.10)	(.20)	(.00)	(.01)	(.00)	(.01)	(.00)
ULS	.82***	2.27***	-.03***	-.07***	-.03***	.08***	.08***
	(.09)	(.22)	(.00)	(.01)	(.00)	(.01)	(.01)
ASF	.29***	1.34***	-.01***	-.02***	-.01***	.02***	.02***
	(.11)	(.15)	(.00)	(.01)	(.00)	(.01)	(.00)
PE	.24*	1.28*	-.01*	-.02*	-.01*	.02*	.01*
	(.13)	(.17)	(.00)	(.01)	(.00)	(.01)	(.01)
CP	.27***	1.31***	-.01***	-.02***	-.01***	.02***	.02***
	(.10)	(.13)	(.00)	(.01)	(.00)	(.01)	(.00)
Observation	439	439	-	-	-	-	-
Pseudo R-Squared	.28	.28	-	-	-	-	-

Note(s). Standard error in the parenthesis *** p<.01, ** p<.05, * p<.1

The results from the ordered logistic regression (Model 1), which estimate the determinants of the frequency of traditional library visits. The model achieves a Pseudo R Square of .28, which is indicative of a moderately good fit for cross-sectional data. The study specifically analyzes the coefficients to identify the nature of the relationship (substitution, complementarity, or independence) between modern digital tools and the demand for physical academic resources in Nepal.

The primary finding concerns the differential impact of digital technologies. The usage intensity of e-learning platforms (e.g., YouTube, educational websites) showed a statistically significant negative coefficient. This result robustly supports the presence of a substitution effect, indicating that students who allocate more time to readily accessible, multimedia-rich digital content are significantly less likely to utilize the traditional library.

Conversely, the time allocated to ChatGPT and other AI-powered tools was statistically insignificant, suggesting that generative AI currently operates as a neutral good or an independent factor regarding physical library demand. This coexistence challenges the notion of universal technology-driven displacement, indicating that AI has not yet achieved sufficient integration into structured academic processes to impact the physical library resources utilization habits.

From a supply-side perspective, the study confirms that investment in physical infrastructure yields positive returns. The quality of traditional library infrastructure was a significant positive predictor of library usage, confirming that well-maintained facilities enhance the utility derived from physical libraries. However, the positive utility derived from infrastructure is partially offset by poor service quality: librarian behavior showed a statistically significant negative association. This finding suggests that unprofessional behavior of library staff imposes a quantifiable negative non-association, demonstrating as a significant deterrent to the consumption of library services, and highlights the necessity of human capital investment alongside physical infrastructure. The core, often non-substitutable, functions of the library were also affirmed, as borrowing physical books and utilizing study space were highly significant positive predictors, highlighting the library's enduring role in providing essential resources and quiet study environments for academic activities.

Finally, the results on academic engagement reveal that library use is strongly driven by mandated coursework and social learning mechanisms. The frequency of assignment submission and peer collaboration both exhibited statistically significant positive effects on library usage. This links physical library visitation directly to the required academic production function and highlights the library's continued importance as a venue for social learning. While the perceived effectiveness of the library also positively predicted usage, students' overall academic performance in exams did not show a direct, significant relationship with usage frequency, suggesting that the library supports the processes of academic effort but that its ultimate impact on final grade outcomes is mediated by more complex, unobserved factors.

Regression Analysis: Models-2, Model-3 and Model-4

Table 3 presents the results of model-2, model-3, and model-4, and the regression analysis. In all 3 models, the R-squared coefficients are above 20% which signifies significant variations explained by the models.

Table 3

Examining the Determinants of Academic Performance, Participation in Research and Writing, and the Average Time Spent Using ChatGPT

Variables	APE	APE	PRP	PRP	ATC	ATC
	Coef.	Log Odd	Coef.	Log Odd	Coef.	Log Odd
EIP	.88*	2.42*	.84*	2.31*	-.30***	.74***
	(.15)	(.363)	(.155)	(.359)	(.089)	(.065)
FTLV	.055*	1.06*	.05	1.05	-.03	.97
	(.052)	(.055)	(.052)	(.055)	(.124)	(.12)
TLI	-.007	.99	.041	1.04	-.27*	.77*
	(.14)	(.14)	(.139)	(.144)	(.092)	(.071)
BPB	.039**	1.04**	.03	1.03	-.21	.81
	(.06)	(.062)	(.06)	(.062)	(.128)	(.104)
ULS	.006	1.02	.041**	1.04**	-.02	.98
	(.03)	(.03)	(.031)	(.032)	(.103)	(.1)
ASF	.326***	1.385***	.31***	1.36***	.17*	1.19*
	(.12)	(.161)	(.12)	(.16)	(.09)	(.11)
PRP	.292***	1.34***	-	-	.38***	1.46***
	(.101)	(.014)			(.13)	(.19)
APS	-	-	.40***	1.5***	.22**	1.24**
			(.104)	(.154)	(.098)	(.122)
Observation	439	439	439	439	439	439
Pseudo R-Squared	.23	.23	.21	.21	.25	.25

Note(s). Standard error in the parenthesis *** *p<.01*, ** *p<.05*, * *p<.1*

Models 2 and 3 examine the relationship between resource utilization and human capital outcomes, using academic performance (APS) and participation in research and writing (PRP) as dependent variables. Across both models, time spent on e-learning platforms exhibits a strong and statistically significant positive association with APS and PRP, indicating high educational returns to internet-based learning resources in developing contexts.

In contrast, ChatGPT usage is statistically insignificant in explaining variation in either outcome. This suggests that, despite widespread adoption, generative AI has yet to achieve a level of pedagogical integration sufficient to generate measurable aggregate academic gains.

Traditional library uses display function-specific effects. Thus, library visitation has a weak positive association with academic performance but no effect on research participation. Disaggregated results reveal that use of library space for reading significantly enhances

research and writing participation, whereas borrowing physical books improves academic performance only, reflecting its primary role in supporting coursework rather than research activities.

Model 4 analyzes the determinants of ChatGPT usage. The results indicate that generative AI adoption is concentrated among academically engaged and high-performing students. Higher levels of research and writing participation, assignment submission frequency, and academic performance are all positively associated with ChatGPT use, suggesting its role as a productivity-enhancing tool for complex academic tasks.

Finally, significant cross-elasticities emerge between ChatGPT and other learning resources. Increased reliance on e-learning platforms and improvements in traditional library infrastructure is both associated with reduced ChatGPT usage, indicating substitution effects. These findings imply that strengthening curated institutional resources, such as digital and physical, may limit over-dependence on generalized AI tools and guide more balanced patterns of educational technology use.

Discussions

The findings offer important insights into patterns of academic resource utilization among higher education students in Nepal, refining existing assumptions in the literature. Contrary to several international studies that report a substitution effect, the use of AI-powered educational tools, specifically ChatGPT, does not exhibit a statistically significant displacement of traditional library usage in the Nepalese context. Rather, the evidence indicates a complementary relationship, suggesting that engagement with generative AI does not reduce students' reliance on physical library resources.

This complementarity can be explained by institutional and contextual factors specific to Nepal. AI integration in higher education remains at an early stage, with limited pedagogical frameworks and uneven institutional adoption, which constrains the capacity of tools such as generative AI to substitute for established academic resources (Rawal, 2025; Sah et al., 2024). At the same time, traditional libraries continue to provide non-substitutable services, particularly access to quiet study environments and essential physical textbooks that are costly or difficult to obtain digitally. Consistent with evidence from comparable developing contexts (Aithal & Aithal, 2023; Narayanan, 2024; Boateng, 2024), these findings suggest that generative AI complements rather than replaces traditional library functions, as it enhances information processing without replicating the broader academic utility of physical library spaces.

In contrast, our analysis reveals a statistically significant negative relationship between the use of e-learning platforms (such as YouTube and educational websites) and traditional library visits. This finding strongly suggests a substitution effect, where increased engagement with these digital platforms reduces the frequency of physical library use. This is economically intuitive: YouTube and educational websites provide an abundance of multimedia content that is easily accessible, highly customized, and often free or low-cost, directly competing with

the informational content and research support offered by libraries. As Boté-Vericad (2025) notes, a digital learning platform serves a dual function for students as a supplementary resource, a role that overlaps considerably with a library's function of providing accessible learning materials. Studies by Maziriri et al. (2020) and Edeh et al. (2020) further highlight the positive academic engagement driven by these platforms. While libraries offer a broader array of services, the primary function of information retrieval for specific academic tasks appears to be increasingly fulfilled by these digital platforms, thereby reducing the marginal utility of a physical library visit for this purpose. This substitution is particularly pronounced in urban areas where internet access is reliable, mitigating the digital divide constraints prevalent in rural regions.

Regarding academic performance, the study finds that e-learning platforms and educational websites are robust positive drivers of student academic performance and research engagement in the Nepalese context. This aligns with a large number of prior studies (Yuhanna et al., 2020; Logan et al., 2021; Ahmad et al., 2023), which highlight their role in facilitating information access, monitoring student progress, developing research skills (such as data analysis), and fostering collaboration. These platforms enhance human capital accumulation by providing flexible learning pathways and access to expert knowledge, thereby contributing positively to educational outcomes.

Conversely, the study finds no significant evidence that ChatGPT or related AI tools currently influence students' academic performance in Nepal, diverging from international studies that report positive effects (Alshater, 2022; Caratiquit & Caratiquit, 2023). This divergence reflects the early stage of AI integration in Nepalese higher education, where concerns over academic integrity, reduced critical thinking, and informational reliability may constrain both institutional endorsement and effective student use (Gödde et al., 2023; Lo, 2023; Sallam, 2023). Consequently, the academic benefits of AI tools remain highly context-dependent and are not yet observable in aggregate performance outcomes.

Finally, a notable finding is the significant negative correlation between the use of educational websites and the use of ChatGPT. This suggests a direct substitution effect, where students who heavily rely on academic websites and YouTube are less dependent on ChatGPT. Students may perceive YouTube, with its visual and expert-curated content, as a more reliable or pedagogically effective tool for specific learning objectives compared to generative AI. This aligns with observations by Zhu (2025) regarding students' perceived effectiveness and limitations of ChatGPT for learning complex skills, and Hussain et al. (2024), who reported an inverse relationship between ChatGPT usage and YouTube engagement.

Conclusion and Implications

The study applies an ordered logistic regression model to cross-sectional survey data from urban higher education students in Kathmandu to examine how the convergence of traditional library services and digital pedagogical tools shapes students' academic resource allocation. This study empirically examined whether emerging educational technologies

serve as complements or substitute for existing academic infrastructure and quantified their impact on human capital outcomes. The result confirms that the effects of digital adoption are highly heterogeneous, presenting a complex challenge for resource prioritization in the Nepalese context.

The findings revealed a clear differentiation in the returns to digital resources. The e-learning platforms significantly impacted academic performance and research engagement while partially substituting for physical library visitation, demonstrating effectiveness and efficiency driven by reallocation of student learning time. This suggests that students rationally substitute the transactional costs of a physical library visit with the easy access and multimedia richness of online platforms, thereby improving overall efficiency in their learning process. Conversely, generative AI tools may not replace the physical library use. This neutrality implies that AI does not transform into human capital formation and academic consumption patterns with the institutional support, ethical governance frameworks, and pedagogical integration.

Theoretically, this study contributes to educational resource allocation by highlighting that the digital learning technology can exhibit complementarity and a differentiated substitution effect rather than uniform disruption. Likewise, this study particularly distinguished between generative AI tools and e-learning platforms, and the results extend resource substitution and human capital theories, were governance structure and institutional maturity drive technology effectiveness. In addition, this study reinforces technology diffusion theory, stating that adoption will not translate into productivity if it's not explicitly integrated with pedagogy and institutional support.

Practically, the higher education institutions in Nepal, the findings demonstrated a need for a holistic investment strategy. The institution should expand access to high-quality e-learning platforms that yield strong academic returns and should be prioritized alongside digital skills training. At the same time, libraries should be strengthened as complementary infrastructure by improving study spaces, maintaining core physical collections, and investing in librarian training to enhance service quality.

Regarding AI governance, institutions should establish clear ethical guidelines and usage frameworks, emphasizing curated, verifiable academic resources over unregulated generative tools. Focusing on a holistic approach can enhance the effectiveness and efficiency of scarce academic resources and support sustainable human capital development.

Limitations and Further Research

Future research could extend the study model in rural educational settings, employing longitudinal or mixed-methods approaches to examine the trends and patterns in educational resources and academic performance. Likewise, future studies could also investigate the discipline-specific effects and students' subjective experiences with generative AI tools and the traditional library.

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Conflicts of Interest

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Appendix

Table A1

Description of the Variables

Vars	Label	Type	Measurement
AGE	Age of respondent	Continuous	Continuous
GEN	Gender of respondent	Dummy	1= male, 0 = Female
FTLV	Frequency of traditional library visits	Continuous	Number of times visited per week
TLI	Traditional library infrastructure	Categorical	Likert scale (5-Point) 1=Very Poor to 5 = Very Rich
LB	Librarian behavior	Categorical	Likert scale (5-Point) 1=Very Rude, to 5=Very Good
BPB	Borrowing of physical books	Continuous	Number of books borrowed per month
ULS	Use of library space	Continuous	Number of hours spent per week
DRTL	Use of Digital resources in the library	Continuous	Number of hours digital resources used per week
ADRTL	Access to digital resources in the library	Categorical	Likert scale (5-Point) 1=No access at all, to 5=Very high access
APE	Academic performance in the exam	Continuous	Average percentage obtained in the last board exam
ASF	Frequency of assignment submission	Categorical	Likert scale (5-Point) 1=never to 5=Always
PRP	Participation in research and writing	Categorical	Likert scale (5-Point) 1=Never to 5=Always
ATC	Average time use of ChatGPT and AI	Continuous	Number of hours spent per week
ElP	Average time spent using E-Learning platforms like YouTube and educational websites	Continuous/ Categorical	
CP	Peer collaboration	Categorical	Likert scale (5-Point) 1=Never to 5=Always

ADR	Access to digital resources	Categorical	Likert scale (5-Point) 1=No access at all, to 5=Very high access
PE	Perceived effectiveness of the library	Categorical	Likert scale (5-Point) 1=Not effective at all, to 5=Very effective

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