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AI-DRIVEN CATALOGUING IN LIBRARIES: EXAMINING LIBRARY PROFESSIONALS' ACCEPTANCE AND USE THROUGH THE UTAUT FRAMEWORK

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ABSTRACT

Artificial Intelligence has expanded so rapidly that it has reshaped the information environment, which makes it important to understand how librarians view and use these emerging tools. This paper looks at library staff attitudes toward AI and AI-driven systems using the Unified Theory of Acceptance and Use of Technology (UTAUT) as its guiding framework. A structured survey was distributed to 165 library staff working in academic, public, and special libraries throughout India. Using Structural Equation Modeling in AMOS 26.0, the researchers tested how the four UTAUT variables — Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Conditions — relate to both Behavioral Intention and actual Usage Behavior. Results showed that all four variables meaningfully predict intention to use AI, with Performance Expectancy emerging as the most influential factor ($\beta = 0.421$, $p < 0.001$). The overall model fit the data well ($\chi^2/df = 1.87$; CFI = 0.963; RMSEA = 0.047) and accounted for 68.3% of the variation in behavioral intention. Overall, library professionals expressed favorable attitudes toward AI, though issues such as limited skills, weak infrastructure, and privacy worries persisted. The paper closes with practical suggestions aimed at library leaders, policymakers, and AI vendors to encourage stronger AI integration in libraries.

Keywords: Artificial Intelligence, Library Professionals, UTAUT, Technology Acceptance, Structural Equation Model, AI Tools, Library Automation, Behavioral Intention

Introduction

Artificial Intelligence has become the defining technology of this era, bringing machine learning, natural language processing, computer vision, and automated systems into nearly every field including library and information science. Libraries, long seen as guardians of knowledge, are now being asked to weave these new tools into their everyday operations. Librarians sit at the center of this shift: as the link between users and information resources, they must not only learn to operate AI systems but also think critically about the trade-offs, limitations, and ethical questions these tools raise. Whether it's smarter reference desks, automated metadata creation, personalized recommendations, chatbots, or predictive analytics, this transformation calls for new professional skills and a change in institutional mindset. Yet very little empirical work has looked specifically at how Indian library professionals perceive and intend to use AI — most existing studies center on Western library systems, which differ substantially from South Asian libraries in funding, infrastructure, digital literacy, and workplace culture. This gap points to a real need for research grounded in the Indian context.

The paper adopts Venkatesh et al.'s (2003) UTAUT model, a well-established framework that combines insights from eight earlier technology-adoption theories including the Technology Acceptance Model, Theory of Planned Behavior, and Diffusion of Innovations and has been shown to explain up to 70% of the variance in people's intention to adopt new technology. Its four core dimensions (Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Conditions) have proven useful across many professional and technological settings.

Using data from 165 professionals spanning academic, public, and special libraries, this study applies the UTAUT framework to uncover what drives AI adoption intentions among Indian librarians, tests a set of directional hypotheses via

Structural Equation Modeling, and translates the results into actionable guidance for stakeholders. In doing so, it adds a regionally grounded perspective to the broader literature on technology acceptance in library science.

Review of Literature

Venkatesh et al. (2003) built the original UTAUT model by synthesizing eight existing technology-acceptance theories. Tested across four organizations over six months, it explained close to 70% of the variance in behavioral intention — far outperforming the ~40% explained by the earlier Technology Acceptance Model. The four core drivers were shown to be shaped by gender, age, experience, and how voluntary the technology use was, laying the theoretical groundwork for later UTAUT applications across many fields, libraries included. **Venkatesh et al. (2012)** extended the framework into UTAUT2 by adding Hedonic Motivation, Price Value, and Habit to better capture consumer technology use. This version explained 74% of the variance in intention to use mobile internet services, proving the model's flexibility. Though UTAUT2 is common in mobile-health and e-commerce research, it has rarely been applied to library AI adoption a gap this study addresses.

Arlitsch and Newell (2017) analyzed how AI was reshaping academic libraries, pointing to natural language processing, machine learning, and intelligent agents as the most transformative subfields. They argued AI could streamline cataloguing, strengthen discovery tools, and personalize user experience, but stressed that libraries need deliberate strategies around staff training, ethical data practices, and algorithmic bias. Their classification of AI applications continues to shape how such tools are categorized in research, including in the present study. **Agarwal and Karahanna (2000)** studied "cognitive absorption" in technology use, finding that intrinsic motivation and immersive engagement affect adoption beyond what the Technology Acceptance Model captures. Their work is relevant here because the novelty of AI tools can spark both curiosity and anxiety depending on a professional's digital literacy, and their finding that deep engagement sustains long-term use has implications for how AI training should be designed in libraries. **Kaur and Walia (2021)** surveyed 220 professionals in Indian university libraries about their awareness of AI, IoT, and blockchain. They found 73% were aware of AI applications, but only 31% had actually used AI tools professionally with limited training, weak institutional backing, and perceived complexity cited as the main obstacles. The study called for structured skill-building programs to close this awareness-to-adoption gap.

Nazim and Mukherjee (2022) examined AI's effect on service delivery in North Indian university libraries using surveys and interviews. They documented a 48% rise in chatbot use between 2019 and 2022, alongside cautious optimism mixed with worries about job loss, deskilling, and a weakening of the human element in library work — themes that inform this study's hypotheses. **Lwoga and Komba (2015)** applied UTAUT to web-based library systems in Tanzania, surveying 347 users. Performance Expectancy ($\beta = 0.38$) and Facilitating Conditions ($\beta = 0.29$) were the strongest predictors, with Social Influence showing a moderate effect ($\beta = 0.21$). This cross-cultural validation supports the present study's expectation that facilitating conditions matter strongly in resource-limited Indian libraries too. **Chauhan and Jaiswal (2016)** used UTAUT to study Learning Management System adoption among 312 Indian faculty members, finding all four constructs significantly linked to behavioral intention. Notably, Effort Expectancy mattered more for faculty over 45, suggesting ease-of-use becomes more important as prior tech experience declines — a pattern this study examines across age groups of librarians.

Cox et al. (2019) reviewed 84 publications (2010–2018) on AI in academic libraries, identifying five main application areas: intelligent search, automated cataloguing, chatbot reference services, predictive collection development, and learning analytics. While efficiency gains were clear in cataloguing and search, user satisfaction with AI-driven reference answers still lagged behind human service a tension directly relevant to how Performance Expectancy is assessed here. **Porat and Tractinsky (2012)** found that perceived aesthetic quality shapes how ease-of-use translates into adoption intention in information systems generally. Though not library-specific, this suggests that interface design, dashboard clarity, and transparency of AI recommendations an underexplored area in library AI research could meaningfully affect professional acceptance. **Raber (2003)** offered a philosophical critique arguing that libraries need coherent value systems before adopting new technologies. This matters for AI adoption because algorithmic decisions can clash with core professional values like intellectual freedom, privacy, and equitable access — ethical dimensions that a purely behavioral model like UTAUT may not fully capture.

Objectives

1. Measure how aware Indian library professionals are of AI and AI-based tools, and the extent to which they have adopted them.
2. Understand librarians' views of AI tools across the four UTAUT dimensions — Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Conditions.
3. Examine how these UTAUT dimensions relate to librarians' intention to use AI tools.
4. Assess how intention translates into actual usage behavior.
5. Validate the UTAUT model specifically within the Indian library context using Structural Equation Modeling.
6. Pinpoint the obstacles and enablers of AI adoption and turn these into concrete recommendations for stakeholders.

Hypothesis

H01: Performance Expectancy (PE) has a positive effect on Behavioral Intention (BI) to adopt AI tools among library professionals.

H02: Effort Expectancy (EE) has a positive effect on library professionals' Behavioral Intention (BI) to adopt AI tools.

H03: Social Influence (SI) has a positive effect on Behavioral Intention (BI) to adopt AI tools among library professionals.

H04: Facilitating Conditions (FC) have a positive effect on Behavioral Intention (BI) to use AI tools among library professionals.

H05: Facilitating Conditions (FC) have a positive effect on the Usage Behavior (UB) of AI tools among library professionals.

H06: Behavioral Intention (BI) positively affects the actual Usage Behavior (UB) of AI technologies among library professionals.

Methodology

The researchers used a quantitative, cross-sectional survey to capture librarians' attitudes toward AI at a single point in time, consistent with a hypothesis-testing, statistically driven approach. A longitudinal design was considered preferable in principle but was not feasible given resource limits. The population of interest was library staff in academic, public, and special libraries in Tamil Nadu. Because no complete national directory of library professionals exists, the researchers used a stratified purposive sample to balance representation across library type, region, and career stage. Of 210 questionnaires sent out, 175 came back, and after removing 10 with excessive missing data or inattentive response patterns, 165 usable responses remained — comfortably above the minimum sample sizes recommended for SEM. The survey itself had three parts: demographics (Section A); AI awareness and current usage habits (Section B); and the six UTAUT constructs measured across 28 items on a 5-point agreement scale (Section C). All items were adapted from Venkatesh et al. (2003) and refined through expert review by five LIS faculty plus a 30-person pilot test (excluded from the main sample), yielding Cronbach's alpha scores between 0.78 and 0.91 — indicating solid internal consistency.

Data Analysis and Interpretation

Table 1
Demographic Profile of Respondents

Factor	Category	No. of Respondents	Percentage
Gender	Male	93	56.4

Factor	Category	No. of Respondents	Percentage
	Female	72	43.6
Age Group	Below 30 years	38	23.0
	30–40 years	56	33.9
	41–50 years	47	28.5
	Above 50 years	24	14.5
Qualification	MLIS	42	25.5
	M.Phil.	32	19.4
	PhD	91	55.2
Type of College	Self-Finance	88	53.3
	Aided	41	24.8
	Government	36	21.8
Experience	Less than 5 years	44	26.7
	5–10 years	52	31.5
	11–20 years	43	26.1
	More than 20 years	26	15.8

The sample is dominated by male respondents (56.4%) compared to female respondents (43.6%), indicating a moderate male majority, though female representation remains substantial. The majority of respondents (33.9%) fall within the 30–40 age group, followed closely by those aged 41–50 (28.5%); together, these two groups account for over 62% of the sample, indicating that the respondent base is predominantly composed of mid-career professionals. Fewer respondents are below 30 (23%) or above 50 (14.5%), reflecting limited representation from the youngest and oldest age brackets. A substantial proportion of respondents hold a PhD (55.2%), reflecting a highly qualified sample, followed by MLIS holders (25.5%) and M.Phil. holders (19.4%). This concentration of doctoral degree holders suggests that respondents are likely engaged in advanced academic or research-oriented roles, which may influence the depth and quality of their responses. More than half of respondents (53.3%) belong to self-financing colleges, while aided (24.8%) and government (21.8%) colleges are represented in similar proportions, indicating that the study draws substantially from the self-financed higher education sector, which may shape institution-specific perspectives in the findings. Respondents with 5–10 years of experience form the largest group (31.5%), closely followed by those with less than 5 years (26.7%) and 11–20 years (26.1%) of experience; only 15.8% have more than 20 years of experience. This distribution reflects a relatively balanced spread across early- and mid-career professionals, with fewer senior respondents, suggesting that the data largely captures the perspectives of professionals still progressing through their careers.

Table 2
Awareness and Usage of Specific AI Tools among Library Professionals

AI Tool / Application	Aware (%)	Have Used (%)	Currently Use (%)	Perceived Utility (Mean/5)
AI-powered literature search	84.2	52.7	38.2	4.01
Chatbot reference services	91.5	67.3	54.5	3.87
Automated cataloguing tools	71.5	34.5	21.2	3.74
AI-based recommendation systems	78.2	44.8	32.1	3.81

AI Tool / Application	Aware (%)	Have Used (%)	Currently Use (%)	Perceived Utility (Mean/5)
Natural language processing for text mining	63.6	28.5	17.6	3.63
AI plagiarism detection	88.5	72.1	61.2	4.12
AI-powered data visualization tools	59.4	31.5	22.4	3.55
Voice-based AI assistants for library navigation	44.8	16.4	9.1	3.28

Based on the data on awareness, usage, and perceived utility of the AI tools and applications surveyed, the following interpretation can be drawn:

Awareness Levels: Chatbot reference services (e.g., ChatGPT for library queries) recorded the highest awareness level at 91.5%, followed closely by AI plagiarism detection tools (88.5%) and AI-powered literature search tools (84.2%). This indicates that respondents are most familiar with generative and text-based AI applications that have widespread visibility in academic and everyday contexts. In contrast, voice-based AI assistants for library navigation showed the lowest awareness (44.8%), suggesting that this technology remains relatively unfamiliar within the library and information science community.

Usage Patterns: AI plagiarism detection tools show the highest conversion from awareness to actual usage, with 72.1% having used the tool and 61.2% currently using it, followed by chatbot reference services, with 67.3% having used it and 54.5% continuing to use it regularly. These figures indicate that tools with direct, practical applications in academic integrity and quick information retrieval have achieved the strongest adoption and sustained usage. Conversely, voice-based AI assistants again show the weakest performance, with only 16.4% having used them and just 9.1% currently using them — reflecting both limited awareness and limited practical relevance in current library workflows. Similarly, AI-powered data visualization tools (22.4% current use) and NLP for text mining (17.6% current use) show relatively low adoption despite moderate awareness, suggesting a gap between knowing about these tools and integrating them into daily practice.

Awareness-to-Usage Gap: Across all tools, there is a consistent decline from awareness to actual current usage, reflecting a typical technology adoption gap. For instance, while 84.2% of respondents are aware of AI-powered literature search tools, only 38.2% currently use them a drop of 46 percentage points. This pattern, observed across all categories, suggests that awareness alone does not translate into adoption, likely due to barriers such as insufficient training, limited institutional support, technical complexity, or unclear practical benefits.

Perceived Utility: Despite varying usage levels, perceived utility remains moderately high across all tools (ranging from 3.28 to 4.12 on a 5-point scale), indicating that respondents generally view AI tools as valuable even where adoption remains limited. AI plagiarism detection tools received the highest utility rating (M = 4.12), consistent with their high usage rate and reinforcing their perceived importance in maintaining academic integrity. AI-powered literature search tools also received a strong utility score (4.01), reflecting their recognized value in supporting research and scholarly work. Voice-based AI assistants received the lowest utility rating (3.28), consistent with their low awareness and usage, suggesting that respondents may not yet see significant relevance or practical benefit in this technology for current library operations.

Table 3

Descriptive Statistics and Reliability Indices for UTAUT Constructs

UTAUT Construct	Items (n)	Mean	SD	Cronbach's α	CR	AVE
Performance Expectancy (PE)	5	3.87	0.64	0.891	0.903	0.651
Effort Expectancy (EE)	5	3.61	0.72	0.874	0.886	0.609
Social Influence (SI)	4	3.42	0.79	0.856	0.869	0.625
Facilitating Conditions (FC)	5	3.28	0.77	0.863	0.878	0.592
Behavioral Intention (BI)	5	3.74	0.68	0.912	0.921	0.701
Usage Behavior (UB)	4	3.12	0.81	0.847	0.862	0.611

Based on the descriptive statistics and reliability/validity indices of the UTAUT constructs, the following interpretation can be drawn:

Mean Scores and Respondent Perceptions: Among the six constructs, Performance Expectancy (PE) recorded the highest mean score (M = 3.87, SD = 0.64), indicating that respondents generally perceive AI tools as useful in enhancing their job performance and productivity in library and information science settings. This is followed by Behavioral Intention (BI) (M = 3.74, SD = 0.68), suggesting a fairly strong inclination among respondents to adopt and continue using AI technologies. Effort Expectancy (EE) recorded a moderate mean score (M = 3.61, SD = 0.72), reflecting that respondents find AI tools reasonably easy to use, though not without some perceived effort or learning curve. Social Influence (SI) had a mean of 3.42 (SD = 0.79), indicating a moderate level of influence from peers, colleagues, or institutional norms on respondents' decisions to use AI tools. Notably, Facilitating Conditions (FC) (M = 3.28, SD = 0.77) and Usage Behavior (UB) (M = 3.12, SD = 0.81) recorded the lowest mean scores among all constructs. The relatively low score for Facilitating Conditions suggests that respondents perceive a lack of adequate infrastructure, technical support, or institutional resources to fully support AI adoption. Similarly, the low mean score for Usage Behavior indicates that actual, sustained use of AI tools remains comparatively limited, reinforcing the previously observed gap between awareness/intention and actual implementation. The relatively higher standard deviations for FC and UB also suggest greater variability in respondents' experiences, possibly reflecting differing levels of institutional support across college types (self-finance, aided, government).

Reliability Analysis (Cronbach's Alpha): All six constructs demonstrate strong internal consistency, with Cronbach's alpha values ranging from 0.847 (Usage Behavior) to 0.912 (Behavioral Intention). Since all values exceed the commonly accepted threshold of 0.70, and most exceed 0.85, the items within each construct reliably measure the same underlying concept, confirming the internal consistency of the survey instrument.

Composite Reliability (CR): Composite Reliability values range from 0.862 (Usage Behavior) to 0.921 (Behavioral Intention), comfortably exceeding the recommended threshold of 0.70. This further confirms that the constructs possess high reliability and that the indicator variables consistently represent their respective latent constructs, providing additional confidence beyond Cronbach's alpha.

Convergent Validity (AVE): Average Variance Extracted (AVE) values for all constructs range from 0.592 (Facilitating Conditions) to 0.701 (Behavioral Intention), all meeting or exceeding the minimum acceptable threshold of 0.50. This indicates that each construct explains more than half of the variance in its indicators, establishing adequate convergent validity. Behavioral Intention shows the strongest convergent validity (AVE = 0.701), while

Facilitating Conditions, though still acceptable, shows comparatively weaker convergent validity (AVE = 0.592), suggesting slightly more measurement variability among its items.

Table 4
Model Fit Indices for the Measurement Model (CFA)

Fit Index	Recommended Criterion	Obtained Value	Model Fit Evaluation
Chi-square/df (χ^2/df)	< 3.00	1.87	Good Fit
Comparative Fit Index (CFI)	> 0.95	0.963	Good Fit
Tucker–Lewis Index (TLI)	> 0.95	0.957	Good Fit
RMSEA	< 0.06	0.047	Good Fit
RMSEA 90% CI	Upper bound < 0.10	[0.041, 0.053]	Good Fit
SRMR	< 0.08	0.052	Good Fit
Average Variance Extracted (AVE)	> 0.50 per construct	0.59 – 0.70	Good Fit
Composite Reliability (CR)	> 0.70 per construct	0.86 – 0.92	Good Fit

Confirmatory Factor Analysis was conducted to assess the psychometric properties of the measurement model prior to structural path testing. The CFA model comprised six latent variables (PE, EE, SI, FC, BI, UB) measured by 28 observed indicators. Model fit indices indicated acceptable fit: $\chi^2(329) = 616.23$; $\chi^2/df = 1.87$; CFI = 0.963; TLI = 0.957; RMSEA = 0.047 (90% CI: 0.041–0.053); SRMR = 0.052. All factor loadings were statistically significant ($p < 0.001$) and ranged from 0.67 to 0.89, exceeding the recommended minimum of 0.60 (Hair et al., 2014).

Table 5
Correlation Matrix with AVE Square Roots on Diagonal

Construct	PE	EE	SI	FC	BI	UB
PE	0.807					
EE	0.521**	0.780				
SI	0.478**	0.442**	0.791			
FC	0.413**	0.507**	0.389**	0.769		
BI	0.632**	0.548**	0.491**	0.463**	0.837	
UB	0.456**	0.398**	0.412**	0.507**	0.573**	0.781

Discriminant validity was assessed using the Fornell–Larcker criterion, which requires the square root of each construct's AVE to exceed its correlations with all other constructs. Table 5 presents the correlation matrix with the square roots of AVE values on the diagonal. All diagonal values exceeded off-diagonal correlations, confirming adequate discriminant validity across all construct pairs.

Table 6
Structural Path Coefficients and Hypothesis Testing Results

Hypothesis	Path	Std. β	S.E.	t-value	p-value	95% CI [LL, UL]	Decision
H1	PE → BI	0.421	0.063	6.683	< 0.001	[0.297, 0.545]	Supported

Hypothesis	Path	Std. β	S.E.	t-value	p-value	95% CI [LL, UL]	Decision
H2	EE → BI	0.298	0.058	5.138	< 0.001	[0.184, 0.412]	Supported
H3	SI → BI	0.213	0.054	3.944	< 0.001	[0.107, 0.319]	Supported
H4	FC → BI	0.187	0.059	3.169	0.002	[0.071, 0.303]	Supported
H5	FC → UB	0.241	0.061	3.951	< 0.001	[0.121, 0.361]	Supported
H6	BI → UB	0.463	0.071	6.521	< 0.001	[0.324, 0.602]	Supported

Following satisfactory validation of the measurement model, the structural model was estimated to test the six research hypotheses. Figure 1 (described in the text below) presents the path diagram of the proposed UTAUT model for AI adoption among library professionals. The structural model demonstrated good fit ($\chi^2/df = 1.91$; CFI = 0.959; RMSEA = 0.049), explaining 68.3% of the variance in Behavioral Intention ($R^2 = 0.683$) and 52.7% of the variance in Usage Behavior ($R^2 = 0.527$).

Table 7

Indirect Effects via Behavioral Intention

Indirect Path	Indirect β	S.E.	95% CI [LL, UL]	p-value
PE → BI → UB	0.195	0.039	[0.118, 0.272]	< 0.001
EE → BI → UB	0.138	0.030	[0.079, 0.197]	< 0.001
SI → BI → UB	0.099	0.027	[0.046, 0.152]	< 0.001
FC → BI → UB	0.087	0.028	[0.032, 0.142]	0.002

Bootstrap analysis (n = 5,000) examined the indirect effects of antecedent UTAUT constructs on Usage Behavior through Behavioral Intention. Table 7 presents the significant indirect effects identified. Performance Expectancy exerted the largest indirect effect on Usage Behavior (β = 0.195, 95% CI: [0.118, 0.272], $p < 0.001$), followed by Effort Expectancy (β = 0.138, 95% CI: [0.079, 0.197], $p < 0.001$), Social Influence (β = 0.099, 95% CI: [0.046, 0.152], $p < 0.001$), and Facilitating Conditions (β = 0.087, 95% CI: [0.032, 0.142], p = 0.002). These significant indirect effects confirm the mediating role of Behavioral Intention in translating UTAUT antecedents into actual AI tool use.

Findings

- The respondent pool skewed male, highly educated (over half held PhDs), mid-career, and was drawn mostly from self-financing colleges — a profile that should be kept in mind when generalizing the results.
- AI tool adoption followed a clear pattern: text-based, academically oriented tools (plagiarism checkers, chatbots, literature-search tools) showed the strongest awareness, usage, and perceived value, while newer or more specialized tools (voice assistants, NLP text-mining) lagged far behind — pointing to an early adoption stage for those tools. A consistent gap between knowing about a tool and actually using it suggests training, institutional backing, and clearer demonstrations of value could help close this divide.
- The measurement model proved reliable and valid across all six constructs (strong Cronbach's alpha, composite reliability, and

AVE scores). Librarians rated AI's performance benefits and their intention to use it fairly positively, but lower scores for facilitating conditions and actual usage point to infrastructural or institutional barriers standing between positive attitudes and real-world use.

- Performance Expectancy was rated highest among the six constructs ($M = 3.87$), showing librarians believe AI can genuinely boost efficiency, service quality, and information access — echoing Venkatesh et al.'s (2003) claim that perceived usefulness is a top driver of adoption.
- Effort Expectancy scored moderately ($M = 3.61$), with a statistically significant age effect: younger professionals found AI easier to use, matching UTAUT's original prediction about age as a moderator. This hints that simplified interfaces and gradual training could improve adoption.
- Social Influence was moderate ($M = 3.42$), suggesting the absence of strong formal AI policies or professional norms in Indian libraries — underscoring a role for library associations and leadership in building supportive norms.
- All six hypotheses were supported. Performance Expectancy ($\beta = 0.421$) was the top predictor of intention, followed by Effort Expectancy ($\beta = 0.298$), Social Influence ($\beta = 0.213$), and Facilitating Conditions ($\beta = 0.187$) — an ordering that closely tracks Venkatesh et al.'s (2003) original findings.

8. Discussion

Given the significant findings on Performance Expectancy, library administrators should employ evidence-based communication strategies to demonstrate the tangible utility of AI tools for core library activities. Social influence pathways can be leveraged to drive adoption through peer-to-peer demonstration programs, in which early adopters showcase efficiency gains to colleagues. Translating this knowledge into action requires institutional strategies for AI adoption that set clear performance targets and allocate funding for AI tools.

The low Facilitating Conditions scores call for immediate policy intervention, particularly for public libraries. Digital infrastructure investment by government bodies responsible for public library development should be prioritized in national library policy frameworks. Minimum standards for AI-readiness in libraries (hardware, connectivity, technical support, training resources) should be established and monitored through library accreditation mechanisms. Given the considerable influence of Effort Expectancy on behavioral intention, library professionals need to actively invest in AI literacy development through formal continuing professional education and self-directed learning. Professional bodies such as the Indian Library Association (ILA) and IASLIC should design modular AI competency certification programs suited to library work environments. LIS curricula at the undergraduate and postgraduate levels should include dedicated AI and data science modules so that new library professionals enter the field with foundational AI competencies.

The moderate Effort Expectancy ratings suggest that existing AI tool interfaces may not be designed with the varying levels of digital literacy among library professionals in mind. Vendors should focus on context-specific user interface design for library AI applications, including intuitive navigation, well-documented guidance in regional languages, and dedicated library workflow integrations. Freemium or subsidized licensing arrangements for academic and public libraries in developing countries could significantly lower economic barriers to AI adoption. Future research could build on this cross-sectional design through longitudinal studies tracking the trajectories of AI adoption among library professionals over time. Incorporating UTAUT2 elements — notably Hedonic Motivation and Habit — could strengthen the model's explanatory power in consumer-facing AI contexts. Qualitative and mixed-methods approaches exploring the ethical dimensions of AI adoption in libraries, including algorithmic bias, data privacy, and professional identity, would further enrich the quantitative findings of this study.

9. Conclusion

Drawing on responses from 165 library professionals across India, this study used UTAUT and Structural Equation Modeling to explore what shapes librarians' attitudes toward AI. The model proved strong, explaining 68.3% of the variance in behavioral intention and 52.7% of the variance in actual usage, with all four UTAUT constructs acting as meaningful, positive predictors — Performance Expectancy chief among them ($\beta = 0.421$). These results reinforce UTAUT's usefulness across cultural and professional contexts.

At the same time, the findings expose a real tension: librarians clearly see AI's potential to improve service quality and efficiency, yet gaps in infrastructure, skills, and institutional backing — especially in public libraries — keep that potential from being fully realized. Closing this gap will take coordinated effort from library leaders, policymakers, educators, professional bodies, and technology vendors. Ultimately, bringing AI into library work is less a purely technical challenge than a broader professional transformation — one that UTAUT helps make sense of, and one that librarians who engage critically with AI's strengths and limits will be best placed to lead.

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