




# Determinants of Artificial Intelligence-Based Library Application Use: A Hybrid Structural Equation Modeling and Neural Artificial Network Analysis

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Article Info	ABSTRACT
<p><b>Article type:</b> Research Article</p> <p><b>Article history:</b> Received 23 February 2026 Received in revised form 6 May 2026 Accepted 8 June 2026 Published online 1 July 2026</p> <p><b>Keywords:</b> artificial intelligence features, perceived usefulness, perceived enjoyment, attitude, use of library applications, artificial neural network.</p>	<p>The purpose of this study was to examine the effect of artificial intelligence features on the use of library applications, with the mediating role of perceived usefulness, perceived enjoyment, and attitude toward the application. The research method was descriptive–correlational and used structural equation modeling. A total of 279 students who use AI-based library applications at universities in Iran participated in this study. Data were collected through a questionnaire. An integrated structural equation modeling and artificial neural network (SEM-ANN) approach was used to analyze the data. The results showed that artificial intelligence features have a positive and significant effect on attitude toward the library application, perceived enjoyment, perceived usefulness, and the use of library applications. Additionally, attitude toward the library application, perceived enjoyment, and perceived usefulness each had a positive and significant effect on the use of library applications. The mediating roles of attitude toward the application, perceived enjoyment, and perceived usefulness in the relationship between artificial intelligence and the use of library applications were also positive and significant. Therefore, it can be concluded that artificial intelligence features increase the use of library applications by improving users’ attitudes, enjoyment, and perceived usefulness.</p>
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## 1) Introduction

The use of library applications has become a core standard for user interaction with modern libraries. These applications focus on a mobile-based user experience and provide instant access to digital collections, subscription databases, and lending services from any place at any time (Rafique et al., 2020; Ying, 2025). Recent studies show that this broad access, especially after the COVID-19 pandemic, has led to a significant increase in the use of electronic resources and user engagement (Sujood et al., 2023). Today's users do more than search and borrow materials through these apps. They manage their personal accounts, reserve study rooms, and receive personalized notifications about due dates or new resources that match their interests. This idea of personalized digital communication improving user engagement is also supported by previous research on personalized advertising in social media environments (Fallahi & Shabestar, 2018). The function of these applications has moved beyond simple transaction management and is now shifting toward building a learning ecosystem and supporting social interaction (Liu, 2025). A multidisciplinary approach to designing digital ecosystems has also been emphasized in recent research on complex service systems (Bevilacqua et al., 2025).

In the digital age, libraries and information centers are rapidly changing toward providing services based on advanced technologies. Among these technologies, artificial intelligence is seen as a key factor that can deeply change how users interact with library resources and services (Vasishta et al., 2025). The expansion of artificial intelligence in information and library services has fundamentally transformed the design and use patterns of library applications. AI-enabled library applications, by offering smart and personalized experiences, have the potential to increase the acceptance and use of these services (Subaveerapandiyan, 2023). Artificial intelligence is shaping the future of libraries and archives around the world while also creating both opportunities and challenges for the library and archival profession (Jabeen, 2025). Scientific studies increasingly highlight the transformative power of artificial intelligence. Pinar and Cox (2025) explain how AI capabilities are redefining cataloging, classification, and archiving practices, while Cox (2023) focuses on the effects of artificial intelligence on professional skills and identity in librarianship. Artificial intelligence and machine learning have also been widely used in other areas such as intrusion detection, business analysis, and financial technology adoption (Bagherabad et al., 2026; Rivandi, 2026; Rivandi & Oskouei, 2025).

The impact of artificial intelligence features on the level and quality of using library applications is considerable. Studies show that AI-enabled applications, by reducing friction in the information discovery process and increasing user satisfaction, significantly improve user interaction and continued use (Barsha & Munshi, 2024). For example, advanced recommender systems help users discover resources that they would likely never find through traditional methods. This increases both the breadth and depth of users' research. In addition, artificial intelligence improves research efficiency by automating complex processes such as organizing search results based on relevance, summarizing key articles, and even predicting users' future information needs (Praveenraj et al., 2025). However, there are important challenges in this area, including algorithmic bias that may limit diversity of viewpoints, privacy concerns related to the analysis of user data, and the need for transparency in how recommender systems work. Research also indicates that individual, social, and organizational factors play an important role in strengthening cybersecurity and protecting digital systems (Nasiri et al., 2026). These issues must be addressed to ensure wide and ethical adoption of this technology in libraries (Mannheimer et al., 2024). The present study aims to examine the effect of artificial intelligence features on users' behavior in using library applications, while considering the mediating role of perceived usefulness, perceived enjoyment, and attitude toward the application. Understanding these mechanisms is essential for designers, librarians, and researchers to improve services and increase technology acceptance.

### **Technology Acceptance Model and UTAUT2**

The Technology Acceptance Model and its extended version, UTAUT2, state that perceived usefulness, attitude, and perceived enjoyment are among the most important requirements for using information technologies. Recent studies on artificial intelligence assistants and AI-based applications show that perceived usefulness, attitude, and perceived enjoyment significantly affect the use of

information technologies (Ali & Warraich, 2024; Parhamnia, 2022; Rafique et al., 2020; Susanto et al., 2020). In the context of library applications, system quality, habit, and effort expectancy have also been found to influence use intention through perceived usefulness, perceived ease of use, and user satisfaction (Rezvani et al., 2022). Perceived usefulness refers to the user's understanding that employing a system improves their performance (Davis, 1989). Artificial intelligence features directly influence this construct. For example, an accurate recommender system can greatly reduce the time and effort needed to find relevant resources, which increases user efficiency (Labrague & Al Harrasi, 2025; Na et al., 2022). Intelligent assistants also make it easier to solve users' information problems by providing immediate access to information and guidance. When users feel that these applications clearly make library-related tasks, such as research, studying, and borrowing, easier and faster, they report a high level of perceived usefulness (Marasinghe et al., 2024; Zondi et al., 2024). This increase in perceived usefulness is considered one of the strongest predictors of the intention to use technology (Hussain et al., 2025; Martono et al., 2020; Moura et al., 2020; Rafique et al., 2020; Sudaryanto et al., 2023).

### **Perceived Enjoyment in the Technology Acceptance Model**

According to the Technology Acceptance Model, perceived enjoyment is one of the factors that influences users' intention to use technology. Perceived enjoyment refers to the positive and pleasant feelings that come from the process of using a technology, regardless of its performance outcomes (Venkatesh, 2000). Feeling enjoyment and happiness while using information technology systems helps users perform their tasks well and finish them on time (Basuki et al., 2022). Artificial intelligence features can strongly influence this aspect of the user experience. Discovering new and interesting resources through smart recommendations can create a sense of curiosity and surprise. Natural and conversational interaction with a friendly chatbot can provide an engaging and low-stress experience (Yuan & Liu, 2025). Intelligent and responsive user interfaces that react to user behavior can give the feeling of interacting with a live and responsive entity. These emotional and engaging aspects turn the use of an application from a purely functional task into an enjoyable experience. Previous research also indicates that beliefs and technology-based visualization tools can positively shape students' learning experiences and engagement (Tazehkand & Safi, 2023). Research has shown that perceived enjoyment plays an important role in technology acceptance. Similarly, recent research indicates that the way a message is framed and how users connect it to their future self can shape positive feelings and engagement with digital content (Safizadeh et al., 2026). Studies confirm a relationship between perceived enjoyment and the behavioral intention to use applications (Basuki et al., 2022; Huang et al., 2024; To & Trinh, 2021; Yuan & Liu, 2025).

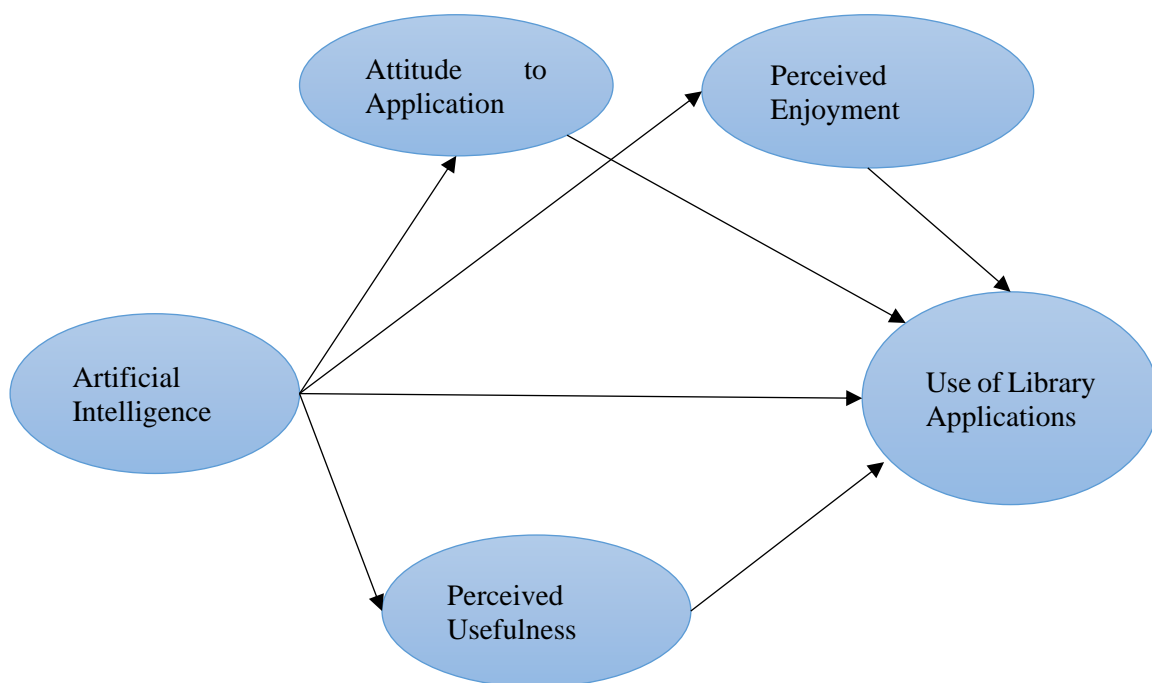
### **Attitude Toward Technology**

Another factor influencing technology use is the user's attitude toward technology. The Theory of Reasoned Action is the most important classic theory linking attitude and behavior, proposed by Fishbein and Ajzen (1975). Attitude toward using an application refers to the user's overall positive or negative evaluation of this behavior (Ajzen et al., 2018). Artificial intelligence features, by simultaneously enhancing perceived usefulness and perceived enjoyment, create a strong and positive attitude. A user who feels that an application helps them while also enjoying the interaction naturally develops a more favorable attitude (Emon & Khan, 2025; Koenig, 2025). According to technology acceptance models, a positive attitude is a key prerequisite for forming the behavioral intention to use a system (Fang et al., 2025; Hussain & Khan, 2025). Dabholkar and Bagozzi (2002) indicated that attitude plays a unique and fundamental role in forming behavioral intentions. Attitude also influences the acceptance and support of technologies as well as technology-related behaviors (Dalbehera, 2018; Jobin & Siegrist, 2020; Liao et al., 2022). Similar evidence suggests that individual knowledge and self-efficacy can shape behavioral outcomes in other domains, such as financial decision-making (Hassani et al., 2025).

Overall, digital transformation has pushed libraries toward offering services through mobile apps. These apps give fast, personalized access to large digital collections and have become essential tools for students and researchers. The rise and spread of artificial intelligence technology have opened new

possibilities for how these apps are designed and how they work. AI promises a deeper change in how users interact with library services. Features like smart recommender systems, virtual assistants, personalization, efficiency, and interactivity significantly improve the apps. This study assumes that AI affects the use of library applications through mediating variables. AI seems to work by improving perceived usefulness, increasing perceived enjoyment, and shaping a generally positive attitude toward the app. These three variables act as key psychological mechanisms, forming a bridge between advanced technology and the user's actual behavior. Identifying and measuring these mediating paths not only helps us understand the theory behind adopting complex technology in educational settings but also gives practical insights for digital service designers, librarians, and policymakers. Evaluating the performance of universities and their digital services using structured decision-making models has also been emphasized in recent research (Talebzadeh et al., 2025). Such understanding allows them to focus on factors that directly affect users' experience and evaluation, rather than just on technical details. Finally, this helps ensure acceptance and effectiveness of large IT investments in libraries.

This research aims to test this conceptual model and fill the gaps in existing literature. Based on the theoretical literature and prior research, the study's conceptual model is illustrated in Figure 1.



**Figure 1. The Research Conceptual Model**

## 2) Research Methodology

The method of this study was descriptive-correlational using structural equation modeling (SEM) and Artificial Neural Networks (ANN) approach. Similar combined modeling approaches, such as SEM integrated with artificial neural networks, have also been used to improve performance analysis in organizational contexts (Heidari et al., 2025). This method was chosen because the study examines the relationships between variables within a structural equation model.

### Population and Sample

The population of this study included students who used AI-based library applications at universities in Iran. A total of 300 questionnaires were distributed among them. Out of these, 279 questionnaires were completed and returned. Among the returned questionnaires, 11 were excluded due to missing data. Finally, 289 valid questionnaires were used for data analysis.

### Data Collection Tools

To measure artificial intelligence features, the questionnaire by Alnaser et al. (2023) was used. This questionnaire has nine items: three items measure trendiness, three items measure visual attractiveness, and three items measure problem solving. To measure perceived enjoyment, the questionnaire proposed by Agarwal and Karahanna (2000) was used, which contains three items. To measure attitude toward the application, the questionnaire by Davis et al. (1989) was used. This questionnaire has four items. To measure perceived usefulness, the questionnaire by Davis (1989b) was used, which includes six items. All items were rated on a five-point Likert scale, ranging from 1 = strongly disagree to 5 = strongly agree. To measure the use of library applications, the questionnaire by Davis et al. (1989) was employed, consisting of four items. These items also used the same five-point Likert scale.

### 3) Findings

#### Measurement Model Testing

To check the reliability of the measurement model, Cronbach's alpha and composite reliability were used. To examine validity, factor loadings, average variance extracted (AVE), and the Fornell–Larcker test were applied.

The composite reliability (CR) index, suggested by Hair et al. (2006), is considered better than Cronbach's alpha. This is because in Cronbach's alpha, all observed variables in a construct are weighted equally, assuming they are equally important. In composite reliability, factor loadings of items are used in the calculation, which reflects their relative importance. As a result, composite reliability values are usually higher and more accurate than Cronbach's alpha. The acceptable threshold for both Cronbach's alpha and composite reliability is 0.70 or above, indicating good internal consistency of the measurement model.

For factor loadings, a value of 0.60 or higher is considered evidence that a construct is well-defined (Chin, 1988). According to Table 1, all factor loadings for the study variables are above 0.60, confirming their validity. It is important to note that if any item has a factor loading below 0.60, it should be revised or removed from the model.

To test convergent validity, the average variance extracted (AVE) was used. Fornell and Larcker (1981) recommend AVE values of 0.50 or higher, meaning that the construct explains at least 50% of the variance of its indicators (Chin, 1988). Table 1 presents factor loadings, composite reliability, and AVE values for all research variables, indicating sufficient reliability and validity of the constructs.

**Table 1. Factor Loadings, Composite Reliability, and Average Variance Extracted of Research Variables**

Variable	Item	Factor Loading	Cronbach's Alpha	CR	AVE
Trendiness	1	0.804	0.661	0.812	0.591
	2	0.73			
	3	0.77			
Visual Attractiveness	1	0.761	0.72	0.843	0.643
	2	0.858			
	3	0.783			
Problem Solving	1	0.842	0.813	0.889	0.728
	2	0.879			
	3	0.838			
Perceived Enjoyment	1	0.839	0.805	0.884	0.717
	2	0.83			
	3	0.871			

Variable	Item	Factor Loading	Cronbach's Alpha	CR	AVE
Attitude to Application	1	0.756	0.805	0.872	0.631
	2	0.842			
	3	0.829			
	4	0.748			
Perceived Usefulness	1	0.719	0.846	0.885	0.564
	2	0.797			
	3	0.815			
	4	0.76			
	5	0.707			
	6	0.7			
Use of Library Applications	1	0.795	0.887	0.922	0.747
	2	0.876			
	3	0.898			
	4	0.885			

### Discriminant Validity

To examine the discriminant validity of the constructs, Chin (1988) suggested two criteria. First, the items of each construct should have the highest factor loading on their own construct and only low cross-loadings on other constructs. Gefen and Straub (2005) recommend that the factor loading of each item on its intended construct should be at least 0.10 higher than its loading on other constructs. Second, the square root of AVE for each construct should be greater than its correlations with other constructs. This shows that a construct is more strongly related to its own indicators than to other constructs. Table 2 reports the cross-loadings of the items on the research constructs.

**Table 2. Cross Loading**

	Artificial Intelligence	Attitude to Application	Perceived Enjoyment	Perceived Usefulness	Use of Library Applications
TR1	0.804	0.336	0.184	0.219	0.186
TR2	0.730	0.309	-0.010	0.100	0.251
TR3	0.770	0.376	0.261	0.254	0.281
VA1	0.761	0.429	0.178	0.227	0.246
VA2	0.858	0.350	0.147	0.258	0.366
VA3	0.783	0.222	0.115	0.240	0.276
PS1	0.842	0.416	0.351	0.515	0.417
PS2	0.879	0.636	0.362	0.556	0.520
PS3	0.838	0.580	0.388	0.409	0.441
AA1	0.498	0.756	0.298	0.358	0.439
AA2	0.599	0.842	0.370	0.373	0.499
AA3	0.503	0.829	0.313	0.433	0.404
AA4	0.462	0.748	0.347	0.546	0.421
PE1	0.288	0.349	0.839	0.525	0.466
PE2	0.232	0.312	0.830	0.588	0.416
PE3	0.390	0.393	0.871	0.578	0.521

	Artificial Intelligence	Attitude to Application	Perceived Enjoyment	Perceived Usefulness	Use of Library Applications
PU1	0.275	0.304	0.648	0.719	0.435
PU2	0.306	0.398	0.612	0.797	0.433
PU3	0.327	0.341	0.630	0.815	0.463
PU4	0.219	0.306	0.659	0.760	0.489
PU5	0.541	0.519	0.325	0.707	0.461
PU6	0.548	0.457	0.404	0.700	0.404
UA1	0.434	0.328	0.522	0.488	0.795
UA2	0.499	0.563	0.434	0.484	0.876
UA3	0.467	0.487	0.470	0.500	0.898
UA4	0.468	0.535	0.505	0.592	0.885

According to Table 2, all dimensions have the highest factor loading on their own construct, and the minimum difference between the loading on their own construct and other constructs is greater than 0.10. This shows that the research constructs have acceptable validity. Table 3 presents the results related to correlation analysis and the second criterion of validity, which is the square root of the AVE.

**Table 3. Correlation Matrix and Square Root of the Average Variance Extracted for the Research Variables**

Variable	Artificial Intelligence	Perceived Enjoyment	Attitude to Application	Perceived Usefulness	Use of Library Applications
Artificial Intelligence	0.78				
Perceived Enjoyment	0.34**	0.85			
Attitude to Application	0.65**	0.41**	0.79		
Perceived Usefulness	0.46**	0.72**	0.51**	0.75	
Use of Library Applications	0.53**	0.55**	0.55**	0.59**	0.86

\*\*P<0.01

### Structural Model Test

To predict the use of library applications, the proposed conceptual model was tested using the SEM method. Based on the research hypotheses, the partial least squares (PLS) approach was used to estimate the model. In addition, the bootstrap method (with 500 subsamples) was applied to calculate the t-statistics and determine the significance of the path coefficients. Figure 2 illustrates the tested model and the relationships between the research variables. The numbers inside the circles represent the explained variance of the research variables.

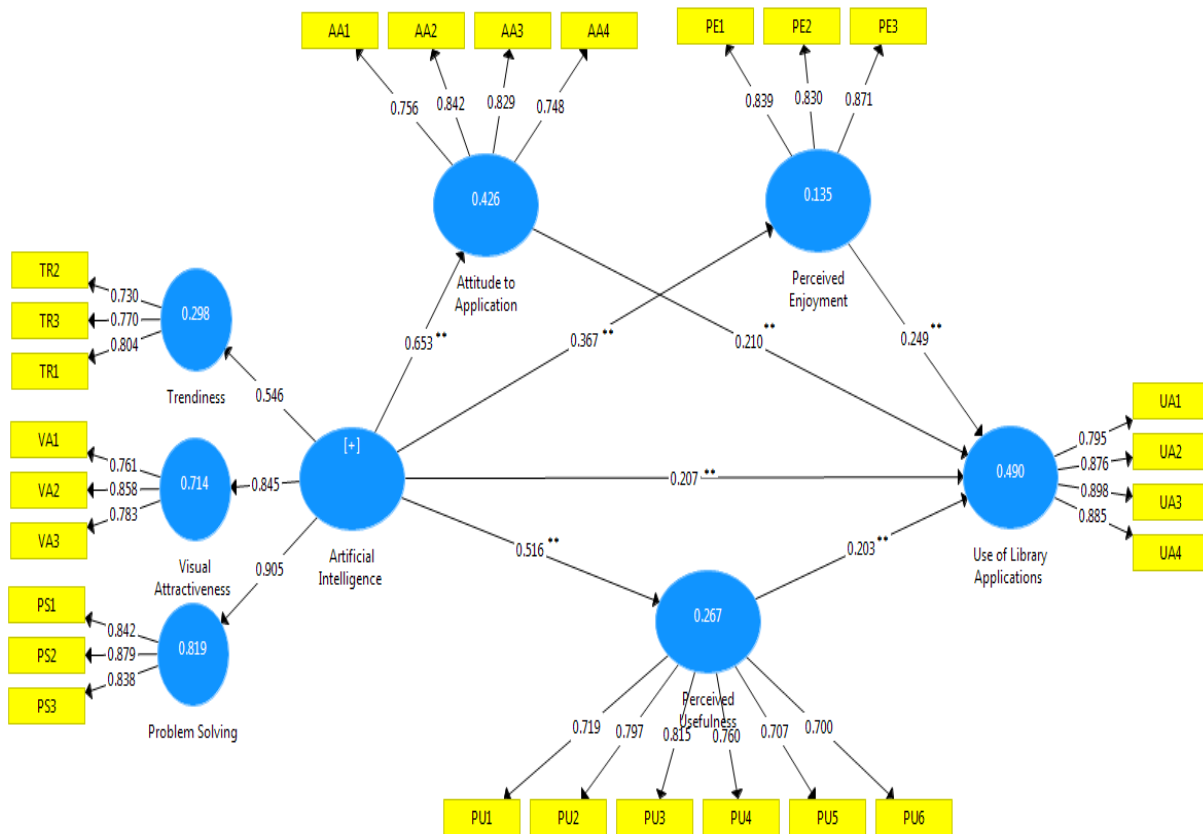


Figure 2. Tested Model of the Use of Library Applications

Table 4 presents the estimated path coefficients and the explained variance of the research variables. The Sobel test was used to examine the significance of the indirect coefficients.

Table 4. Path Coefficients and Explained Variance

Paths	Path Coefficients	t-values	Explained Variance
Effects on Use of Library Applications from:			
Artificial Intelligence	0.207**	3.761	0.49
Perceived Enjoyment	0.249**	3.124	
Attitude to Application	0.210**	3.04	
Perceived Usefulness	0.203**	2.760	
Effects on Attitude to Application from:			
Artificial Intelligence Features	0.653**	17.281	0.426
Effects on Perceived Enjoyment from:			
Artificial Intelligence Features	0.367**	4.691	0.135
Effects on Perceived Usefulness from:			
Artificial Intelligence Features	0.516**	8.683	0.267

\*p<0.05, \*\*p<0.01

As shown in Table 4, artificial intelligence features exert positive and significant effects on attitude toward the library application, perceived enjoyment, perceived usefulness, and the use of library applications.

The effect of attitude toward the library application on the use of library applications is also positive and significant. Likewise, perceived enjoyment has a positive and significant effect on the use of library applications. The same result is found for perceived usefulness, which also positively and significantly influences the use of library applications. In addition, the variables in the research model explain 49% of the variance in the behavioral use of library applications, 43% of the variance in attitude toward the application, 13% of the variance in perceived enjoyment, and 27% of the variance in perceived usefulness. The indirect coefficients are reported in Table 5.

**Table 5. Indirect Coefficients**

Indirect paths	Indirect Effects	T Statistics	P Values
Artificial Intelligence -> Attitude to Application -> Use of Library Applications	0.137	3.058	0.002
Artificial Intelligence -> Perceived Enjoyment -> Use of Library Applications	0.091	2.775	0.006
Artificial Intelligence -> Perceived Usefulness -> Use of Library Applications	0.105	2.603	0.01

As shown in Table 5, the mediating role of attitude toward the application in the relationship between artificial intelligence and the use of library applications is positive and significant. The mediating role of perceived enjoyment in the effect of artificial intelligence on the use of library applications is also positive and significant. In addition, perceived usefulness plays a positive and significant mediating role in this relationship.

The overall model fit index in PLS is the Goodness of Fit (GOF) index, which is used to evaluate the overall quality and validity of the PLS model. In the present study, the GOF value for the tested model was 0.53. This value indicates a good fit for the model.

#### **ANN Results**

The ANN analysis was carried out using the neural network module in IBM SPSS. We used a feed-forward backpropagation model with a multilayer perceptron (MLP) structure. The input variables were the important predictors that were identified earlier from the PLS-SEM results. To make the results more reliable and avoid overfitting, we applied a 10-fold cross-validation approach. This means we ran the ANN model ten separate times. The sigmoid function was used as the activation function for both the hidden layer and the output layer. The number of hidden nodes was selected automatically by SPSS. The final model had one hidden layer with three neurons, as shown in Figure 3. The data were divided into two parts: 80% for training the model and 20% for testing it. Model performance was evaluated using the root mean square error (RMSE). The RMSE values were 0.116 for the training data and 0.114 for the testing data (see Table 4). These low values show that the model fits the data well and performs consistently on new data. We also conducted a sensitivity analysis to examine the importance of each predictor. As shown in Table 7, AI features were the most important predictor (100%). This was followed by perceived enjoyment (79.61%), perceived usefulness (65.12%), and attitude toward the application (51.15%).

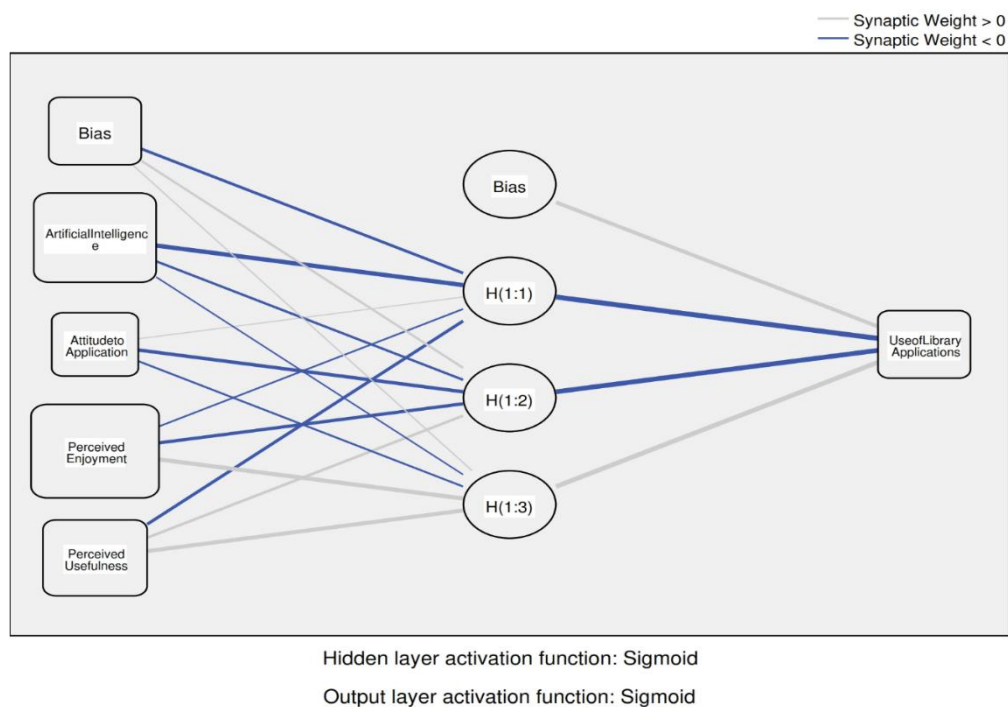


Figure 3. Artificial Neural Network Arcitecture

Table 6. RMSE Values and Sensitivity Analysis

Training			Testing			Sensitivity analysis				
N	SSE	RMSE	N	SSE	RMSE	Neural Networks	AI	Attitude to Application	Perceived Enjoyment	Perceived Usefulness
220	2.75	0.11	59	1.09	0.14	ANN 1	0.34	0.15	0.17	0.34
225	2.94	0.11	54	0.78	0.12	ANN 2	0.32	0.20	0.23	0.26
230	3.28	0.12	49	0.46	0.10	ANN 3	0.28	0.29	0.24	0.20
224	2.71	0.11	55	1.07	0.14	ANN 4	0.32	0.19	0.30	0.19
219	2.83	0.11	60	0.87	0.12	ANN 5	0.31	0.19	0.28	0.22
229	3.03	0.12	50	0.82	0.13	ANN 6	0.38	0.18	0.31	0.14
212	2.83	0.12	67	0.69	0.10	ANN 7	0.37	0.16	0.24	0.22
231	3.54	0.12	48	0.34	0.08	ANN 8	0.50	0.06	0.28	0.16
218	3.21	0.12	61	0.71	0.11	ANN 9	0.26	0.18	0.32	0.25
216	3.06	0.12	63	0.64	0.10	ANN 10	0.31	0.14	0.33	0.22
Mean	3.02	0.12	Mean	0.75	0.11	Mean Importance	0.34	0.17	0.27	0.22
SD	0.25	0.00	SD	0.22	0.02	Normalized Importance	100.00	51.15	79.61	65.12

#### 4) Discussion and Conclusion

The present study was conducted to examine the effect of artificial intelligence features on the use of library applications, with the mediating roles of perceived usefulness, perceived enjoyment, and attitude toward the application. The results showed that the proposed model has a relatively good fit with the research data and can explain 49% of the behavioral variance in the use of library applications.

The findings also showed that artificial intelligence has a positive and significant effect on the use of library applications. This result suggests that integrating smart capabilities into library software clearly increases users' willingness to interact with these platforms. One possible explanation is that artificial intelligence improves efficiency and simplifies processes such as searching for resources, offering personalized recommendations, and providing intelligent support. By doing so, it reduces the traditional barriers to using digital library services. Similar findings in educational settings show that AI-based predictive tools can reduce failure and dropout rates by identifying learning problems early (Tazehkanda & Wanga, 2024). Similarly, analyzing uncertainty and using early warning systems is crucial in financial markets (Gudarzi Farahani et al., 2026; Roshdieh, 2024). In this regard, Firoozabadi et al. (2024) showed that machine learning models, especially SVM, can improve crude oil trend prediction during uncertain periods such as the COVID-19 pandemic. Integrated approaches that combine structural equation modeling and artificial neural networks have also been applied to predict complex market reactions (Khorsand et al., 2026). Similar data-driven methods have also been used to analyze and classify human behavior in other areas, such as driving behavior recognition using Bayesian models (Pourghasemi et al., 2026).

As a result, users' understanding of the usefulness and ease of employing the application improves, which is an important factor in technology acceptance and use. In addition, features such as recommendation systems based on individual usage patterns and responsive chatbots that provide real-time guidance create a sense of smart support and personalized interaction. This aspect of user experience, which goes beyond simply meeting information needs, likely plays an important role in increasing satisfaction and continued use. Therefore, it can be concluded that artificial intelligence changes service delivery from a passive and uniform form to an active and customized one, which increases the inherent attractiveness of library applications.

The results showed that artificial intelligence has a positive and significant effect on users' attitude toward library applications. This suggests that the more AI-based technologies are used in the design and operation of these applications, the more users develop trust, interest, and willingness to use them. Research confirms that consumer trust in AI and moral considerations play a key role in shaping adoption intentions (Pezeshgi et al., 2025a). In educational settings, digital service adoption has also been linked to trust, brand perception, and user engagement mechanisms (Khorsandi et al., 2025). Smart capabilities make the user experience simpler, more personalized, and more efficient. This positive experience naturally leads to a more favorable attitude toward the application. In other words, combining artificial intelligence with library services allows complex tasks such as searching for resources, receiving recommendations, and getting answers to questions to be completed faster and with greater accuracy. As a result, users gain a stronger sense of the system's usefulness and value. This finding is consistent with user behavior theories in technology, suggesting that a positive attitude is often an important step toward the acceptance and continued use of new technologies.

The results indicated that artificial intelligence has a positive and significant effect on perceived enjoyment. This finding suggests that AI-based technologies have improved the user experience in a positive way, so users feel more satisfied, motivated, and engaged when using these applications. Features such as smart resource recommendations, faster and more accurate search, and personalized content help users feel that the system understands their needs and interests in an intelligent way. Studies also suggest that AI-driven personalization can strongly influence users' decisions and behavioral responses in digital environments (Pezeshgi et al., 2025b). Consequently, users perceive the application as more enjoyable and effective, which increases the likelihood of continued use. This finding can help designers of digital library systems. It suggests that future designs should focus on using artificial intelligence to improve both the emotional and cognitive experiences of users.

The results showed that AI positively and significantly affects users' perceived usefulness. This agrees with the studies of Na et al. (2025) and Labrague and Al-Harrasi (2025). It means that users see AI-based library applications as more helpful and efficient for accessing information and completing library tasks. When users feel an application is useful, they are more likely to adopt it. This is because it shows that the system can make their work easier and better. AI improves the user experience by offering features such as natural language search, personalized recommendations, and virtual assistants. These tools make the experience smoother, more interactive, and give users a sense of control while reducing the mental effort needed to search and find information. AI also helps by automating time-consuming tasks, such as sorting search results or filtering resources, and giving helpful guidance when needed. In educational contexts, automated AI systems have also been shown to support formative assessment and improve students' ability to articulate their ideas (Karizaki et al., 2024). These features make users feel that the app works efficiently and meets their needs effectively.

The results showed that attitude toward the application has a positive and significant effect on the use of library applications. This finding aligns with the studies of Dalbehera (2018), Jobin and Siegrist (2020), and Liao et al. (2022). This result is also consistent with theoretical frameworks of technology acceptance, which consider attitude as a key prerequisite for actual behavior. In other words, when users have a more positive overall evaluation of the app, they are more likely to use it repeatedly and voluntarily. A positive attitude generally arises from a combination of beliefs about the app's usefulness and pleasant emotional experiences during interaction. A user who finds the application efficient, useful for academic or personal goals, and also attractive and easy to use, develops a positive psychological tendency toward it. This tendency, in turn, provides the motivation needed to overcome minor usage obstacles (such as initial learning or time required) and makes actual use easier.

The results showed that perceived enjoyment has a positive and significant effect on the use of library applications. This finding is consistent with the studies of Huang et al. (2024), Basuki et al. (2022), To and Trinh (2021), and Yuan and Liu (2025). This result, which aligns with recent extensions of technology acceptance models (such as UTAUT2), highlights that users' intrinsic and emotional motivations, along with practical and useful considerations, play an important role in predicting their actual behavior. In other words, when interacting with a library app generates positive feelings such as pleasure, fun, or inherent attractiveness, the likelihood of continued and repeated use significantly increases. Many library tasks and information search activities can come with cognitive and sensory fatigue. In this context, elements such as visually appealing interface design, interactive and gamified mechanisms, or smart content personalization that make the experience enjoyable, can reduce this cognitive load. These elements turn using the app from a simple task into an engaging and enjoyable experience.

The results showed that perceived usefulness has a positive and significant effect on the use of library applications. This finding is consistent with the studies of Moura et al. (2020), Martono et al. (2020), Rafique et al. (2020), and Hussain et al. (2025). This result indicates that users' perception of the usefulness of a library application plays a central role in predicting their actual use of it. This finding aligns fully with theoretical foundations in the field of technology acceptance, which have always emphasized that belief in usefulness is the strongest behavioral motivator. In the context of library services, perceived usefulness goes beyond a general concept and usually appears in forms such as saving research time, increasing the accuracy of information retrieval, facilitating access to full-text resources, or simplifying borrowing processes and personal reference management. When a user believes that using the application truly improves their effectiveness in performing these tasks, they are more likely to rely on it and continue using it over time.

### **Limitations and Future Directions**

The first limitation is about who was studied and how the sample was chosen. We tried to select a large and varied group of students from universities in Iran. The study focused only on students. Therefore, we should be careful when applying the results to other users of library apps, like professors, researchers, librarians, or public library users. These groups may have different needs, motivations, and digital skills than students. This could change how they see the usefulness or enjoyment of AI tools.

Future studies should include other groups, such as faculty, researchers, graduate students, or public library users. This would help us understand how AI features affect different kinds of users.

The second limitation is about how the data were collected. We used self-reported questionnaires at one point in time. This kind of design can test relationships between variables, but it cannot prove cause and effect. It only shows what variables are related at that time. Future studies should use long-term research to see how users' thoughts and behavior change over time. Additionally, self-reported data can be biased. For example, individuals might answer in a way that makes them look good, or they might forget things. Using mixed methods, like combining surveys with interviews or observations, can help fix this problem.

The third limitation concerns the variables we studied, particularly three main ones, including perceived usefulness, perceived enjoyment, and attitude. We chose them based on strong theory, but other important variables, such as trust in AI, privacy concerns, social norms, and digital literacy of users, were not studied. Demographic factors, such as age, gender, field of study, and previous experience with technology, were also not considered as moderators. Leaving out these variables may explain part of the unexplained differences in how individuals use library apps.

### Practical Findings

The findings of this study, besides helping theory, give clear practical advice for stakeholders in digital library services.

The first group that can benefit is designers and developers of library apps. Since perceived usefulness has a strong effect on usage, developers should focus on improving AI features that help users work more efficiently and effectively. Recommendation systems that suggest resources based on a user's search history, borrowed items, and research interests can save time and help users find articles and books they might miss in normal searches. Using semantic search algorithms that understand complex questions, even with spelling mistakes, can also make the app more useful.

Moreover, since perceived enjoyment plays an important role, designers should focus on user experience beyond basic functions. This can be done by making a smooth, easy-to-use, and attractive interface, adding gamification features (e.g., badges, points, and reading challenges), and enabling chat-like interactions with smart assistants. These features can turn using the app from a boring task into a fun and even engaging activity. Showing how the algorithms work and giving simple explanations for recommendations can build trust and improve attitudes. Developers should treat algorithms as transparent helpers, not "black boxes."

Library managers and librarians are very important for the success of smart library apps. The first step is helping users improve their digital and AI skills. Many users, especially students in early semesters, are not fully aware of all the smart features in library apps. Short workshops, instructional videos, and in-person guidance in the first weeks of the semester can help users understand the features and their usefulness. Librarians should also collect feedback actively. By talking directly to users, they can find the app's strengths and weaknesses and share this with the technical team. At the same time, promoting responsible data use and emphasizing privacy will assist users in trusting the system and sharing the data required for AI.

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