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Factors influencing users' attitudes towards intelligent chatbots in Chinese academic libraries: the role of algorithm literacy

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This study explores the mechanism of the effect of algorithm literacy of Chinese academic library users on the attitude towards using library intelligent chatbots. The mixed research paradigm of convergent design is drawn upon by this study, a research model based on the Technology Acceptance Model and perceived risk theory is constructed, and questionnaire data and interview data are collected for analysis. There are three findings. First, the algorithm literacy of users themselves and the perception formed in the process of contact with library intelligent chatbots are important factors affecting their attitude towards use. Second, the effect of algorithm literacy on attitude is mediated by perceived efficiency and perceived risk. Lastly, People with higher algorithm literacy may hold more positive attitudes toward intelligent chatbots. This study reveals how algorithm literacy influences users' interactions with AI technology, providing a novel perspective for the study of library intelligent chatbots usage. Practically, this study offers references and insights on effectively applying users' algorithm literacy to enhance chatbots user acceptance and service quality.

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Introduction

Artificial Intelligence (AI) greatly changed people's lifestyles and is widely applied in academic libraries. As a significant application of AI technology in the development of academic libraries, intelligent chatbots offer efficient and proactive interactive services to readers around the clock (Li and Coates, 2024; Panda and Chakravarty, 2022). They are changing the pattern of library and information services (Aboelmaged et al., 2024). Academic libraries can successfully develop and train AI chatbots, such as Engati (Panda and Chakravarty, 2022), Bcpylib (Thalaya and Puritat, 2022) and "Xiao Tu" of Tsinghua University. However, in stark contrast to the rapid advancement of AI technology, users' attitudes towards these AI systems vary widely. The adoption rate of intelligent chatbots in libraries is relatively low (Guy et al., 2023; Twomey et al., 2024). A survey of 1035 Chinese librarians revealed that only 36.81% reported their libraries had adopted intelligent chatbots (Zhao et al., 2025). This lag in technology adoption requires deeper investigation. The success of technology implementation largely depends on whether end users are willing to accept and use it. Therefore, in the library context, understanding how users perceive and interact with intelligent chatbots is essential for improving adoption rates. There is considerable interest in the application of chatbots in libraries (Allison, 2012; Panda and Chakravarty, 2022). But the motivation for users to use such tools has only been explored within a limited scope.

Some studies have employed the Technology Acceptance Model (TAM) to explore the influencing factors of accepting intelligent chatbots (Awal and Haque, 2024; Bilquise et al., 2024; Pillai et al., 2024). For example, one study investigated users' attitudes toward academic advising chatbots. All the respondents have indicated an average to a good experience with technology (Bilquise et al., 2024).

However, the library chatbots are designed to assist users with specific queries related to library resources and services. They aim to provide targeted and efficient support. Additionally, Ordinary users' fear of technology, distrust stemming from the opacity of algorithm operations, and the potential learning burden. These factors may all influence their acceptance of intelligent chatbots (Bohle, 2018). Algorithm literacy may influence people's views on artificial intelligent system (Shin et al., 2022), but it has not been integrated into the TAM. Algorithm have become commonplace in our life. Algorithmic literacy plays a crucial role in academic library education (Archambault et al., 2024). Therefore, adopting a new framework to explore the role of user algorithm literacy in shaping attitudes towards library intelligent chatbots is of great importance. This can effectively supplement the deficiencies in empirical research on chatbot user experience in the development of academic library. This study addressed the following two questions:

RQ1: How does algorithm literacy among academic library users shape their attitudes towards intelligent chatbots?

RQ2: What is the impact of demographic characteristics on various variables (such as algorithm literacy, user perception, and attitudes towards library intelligent chatbots usage)?

Literature review

Library intelligent chatbots. Currently, research on library chatbots is still in the early exploratory stage (Yan et al., 2023). Most studies primarily focused on the theoretical exploration of service functions (Adetayo, 2023; Sanji et al., 2022), system development and implementation (Ehrenpreis and DeLooper, 2022; Panda and Chakravarty, 2022; Rodriguez and Mune, 2022; Thalaya and Puritat, 2022) and application case analysis in intelligent service scenarios (McKie and Narayan, 2019; Vincze, 2017). Existing research primarily emphasizes technical implementation and functional design. These studies provide practical cases. However, exploration of user acceptance and usage behavior remains notably insufficient.

Research on the factors influencing the use of intelligent chatbots in libraries is relatively limited. Kaushal and Yadav (2022) have explored user experiences and usage motivations using qualitative methods. Their findings indicated that everyone was also concerned about the numerous risks this adoption would bring. Wang et al. (2023a) have empirically studied the influencing factors of user behavior based on the functions and social characteristics of robots. It was found that user trust significantly influences user adoption behaviors Safadel et al. (2023) found that perceived usefulness and perceived ease of use influenced people's intentions to use library virtual chatbots. The literature shows no scholars have yet studied attitudes towards the use of intelligent chatbots in libraries from the perspective of user literacy. To further enrich understanding of users' motivations for adopting library AI chatbots, this study employs a mixed-methods approach for analysis.

Algorithm literacy. Algorithm literacy refers to an individual's ability to understand, evaluate, and apply algorithms. It is a potential factor influencing users' attitudes towards the use of intelligent systems (Deng et al., 2023). Algorithm literacy first requires individuals to be aware of the existence of algorithms, understand their significant influence (Swart, 2021), and be able to infer the functions of algorithms (Rieder, 2017; Dogruel et al., 2022). Secondly, there is a need for critical evaluation of algorithmic decisions and skills to address or even influence algorithmic operations (Koenig, 2020). Simultaneously, we must emphasize the importance of algorithmic social norms. This helps address and prevent negative impacts of algorithms. Accordingly, this study follows Deng (2023) research. It divides algorithm literacy into algorithm awareness (AA), algorithm knowledge (AK) and skills, critical thinking (CT) and algorithm social norms (ASN) for further study.

In the field of intelligent chatbots applications, algorithm literacy includes a fundamental understanding of technology. It also covers an awareness of how algorithms process personal data and deliver personalized services. This highlights the importance of AI literacy including algorithm literacy (Archambault et al., 2024; Kim, 2023). This positions algorithm literacy as a critical dimension in assessing and explaining users' attitudes towards intelligent chatbots. Especially in the transition of library services from informatization and digitalization to intelligent and smart systems, the importance of algorithm literacy is self-evident (Archambault et al., 2024; Wu D., 2022).

Academia has paid attention to the role of user qualities in the adoption of digital technologies. Most studies focused on information literacy (Nikou et al., 2022), and health literacy (Yi-No Kang et al., 2023) and digital literacy (Cetindamar et al., 2021). It remains unclear how algorithm literacy influences users' attitudes towards technology use. Existing research on algorithm literacy primarily focuses on its connotations of algorithm literacy (Archambault et al., 2024; Xia et al., 2023), scale design (Dogruel et al., 2022), and the development of evaluation systems (Deng et al., 2023). But there is a lack of systematic research on the mechanism between algorithm literacy and users' attitudes towards using intelligent chatbots. So, it is necessary to study the factors influencing the use of intelligent chatbots by academic library users from the perspective of algorithm literacy.

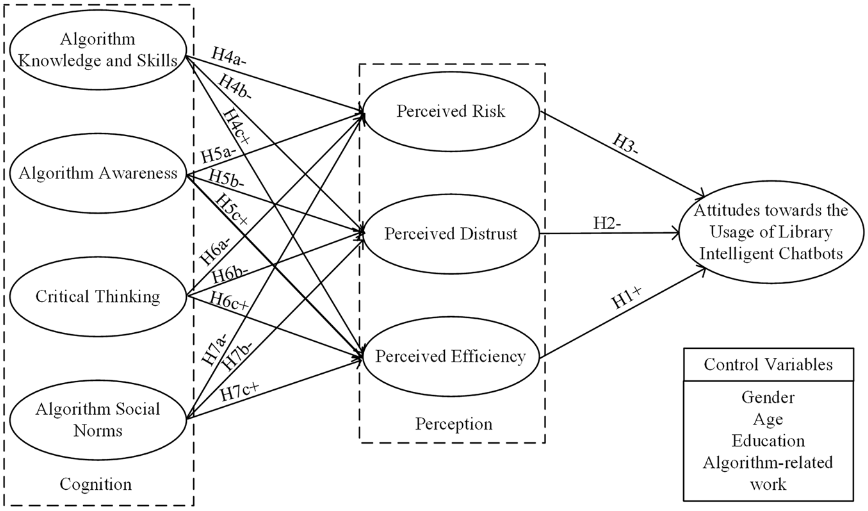

Fig. 1 Research Model.

Technology Acceptance Model (TAM). The TAM is a theory proposed by Davis (1989) to explain user technology usage behavior. TAM emphasizes that users' perceived usefulness and perceived ease of use of new technology directly influence their attitude towards using the new technology, and further affect their behavior. TAM has been validated through numerous empirical studies. It demonstrates good predictive power in various contexts, such as health information technology acceptance behavior (Yi-No Kang et al., 2023) and shared electric bicycle adoption intentions (Pan et al., 2022). However, technological environments continue to develop. User needs are also becoming more diverse. Relying solely on perceived usefulness and perceived ease of use may not fully explain users' technology acceptance behavior.

In terms of AI device adoption, Dahri et al. (2024) integrated factors such as perceived AI trust and perceived AI capability into the TAM to study ChatGPT usage behavioral intentions. Ezeudoka and Fan (2024) studied the influence of factors such as trust and performance expectancy on e-pharmacy usage behavior, extending the TAM. These new factors demonstrate strong explanatory power for users' AI device usage behavior.

This study will take this model and incorporate perceived trust, perceived risk (PR), and perceived efficiency (PE) as mediating variables. It examines the relationship between users' algorithmic literacy and their perception and usage attitudes towards academic library intelligent chatbots. This relationship has been largely overlooked in prior literature.

Theoretical foundation and hypotheses development

Existing literature supports the feasibility of adopting TAM. Safadel et al. (2023) applied TAM to study factors influencing intelligent library chatbots. So, TAM is employed as the theoretical framework for this study. The framework includes four cognitive variables. They are algorithm knowledge and skills (AK), AA, CT, ASN. The framework also contains three perceptual variables and one dependent variable. They are PR, perceived distrust (PD), PE and attitude towards usage (UA). Additionally, gender, age, education, and involvement in algorithm-related work are considered as control variables. Figure 1 explains the study's proposed research model.

Perceived efficiency and perceived distrust. Within the TAM framework, users are more inclined to use technologies they believe will improve work efficiency and quality of life. Previous studies show that PE significantly predicts an individual's behavior intention to AI of library (Yang et al., 2024; Zhang et al., 2016).

Furthermore, trust is a key psychological factor driving user acceptance and use of technology. Empirical research results by Eren (2023) and Wang et al. (2023a) show that trust is the most important factor affecting the willingness to use robotic advisors.

Accordingly, this study proposing the following hypotheses:

H1: Users who perceive higher efficiency associated with library intelligent chatbots will exhibit a more positive attitude towards their use.

H2: Users who perceive higher levels of distrust associated with library intelligent chatbots will exhibit a more negative attitude towards their use.

Perceived risk theory (PRT). The PRT describes consumers' assessment of potential negative outcomes before purchasing products or services (Barach, 1969). Scholars in the field of information systems point out that PR significantly influences individual adoption of technology (Kesharwani and Singh Bisht, 2012; Im et al., 2008).

The AI technologies and algorithms employed by chatbots are like a "black box" to users. The potential risks faced by users may include privacy breaches, data security, and the risk of erroneous information (Featherman and Pavlou, 2003). Users of library intelligent chatbots may perceive high risks, such as concerns about mishandling sensitive information. They might also worry about receiving inaccurate information that could lead to incorrect decisions. These risk perceptions can negatively influence their attitude towards using the technology (Kaushal and Yadav, 2022).

PR also includes users' concerns about the consequences of technology failure, such as service interruptions and poor user experience (Trivedi, 2019). If users prioritize these risks over the anticipated benefits of the technology, their attitudes may turn negative. This shift in attitude stems from worries about possible negative outcomes.

Accordingly, this study proposes the following hypothesis:

H3: Users who perceive higher risks associated with library intelligent chatbots will exhibit a more negative attitude towards their use.

Algorithm literacy. The cultivation of algorithm literacy can help people recognize the potential risks of algorithms and improve their ability to prevent and combat these risks. Xu and Cheng (2022) found that many users are ignorant about algorithms but hold negative evaluations. In contrast, digital natives with higher algorithm cognition perceive fewer algorithmic risks. Most users are unaware of how these platforms operate in daily life (Cheney-Lippold, 2011). If they knew, users would become increasingly concerned about the impact of these algorithmic platforms on our daily interactions (Just and Latzer, 2017). It can be hypothesized that when users have higher algorithm literacy, they will perceive lower risks from intelligent chatbots.

Accordingly, this study proposes the following hypotheses:

H4a: Users with higher levels of algorithm knowledge and skills will perceive lower risks associated with library intelligent chatbots;

H5a: Users with higher levels of algorithm awareness will perceive lower risks associated with library intelligent chatbots;

H6a: Users with higher levels of critical thinking will perceive lower risks associated with library intelligent chatbots;

H7a: Users with higher levels of algorithm social norms will perceive lower risks associated with library intelligent chatbots.

Trust is a construct that describes the perception or belief that people, organizations, or technologies are credible, trustworthy, and reliable (Winkler and Söllner, 2018). It is a crucial factor in establishing and maintaining effective interactions with robots. PD in this study refers to users' lack of trust in intelligent chatbots. Swart (2021) argues that understanding and mastering algorithm-related knowledge can lead individuals from negative emotions and distrust to positive emotions and appreciation of technology. Research has shown that individual algorithm literacy affects their trust in robots (Montal and Reich, 2017).

Accordingly, this study proposes the following hypotheses:

H4b: Users with higher levels of algorithm knowledge and skills will perceive lower levels of distrust associated with library intelligent chatbots;

H5b: Users with higher levels of algorithm awareness will perceive lower levels of distrust associated with library intelligent chatbots;

H6b: Users with higher levels of critical thinking will perceive lower levels of distrust associated with library intelligent chatbots;

H7b: Users with higher algorithm social norms will perceive lower levels of distrust associated with library intelligent chatbots.

PE refers to an individual's subjective assessment of the efficiency improvement brought by a certain technology, tool, or service (Moon and Lee, 2022). Petrič et al. (2017) found that mastery of modern information technology knowledge contributes to enhancing PE. Yi-No Kang et al. (2023) examined digital literacy and health promotion knowledge significantly influence the PE of AI. Algorithm literacy improves users' comprehension of how intelligent chatbots operate, helping them assess the efficiency benefits, potentially influencing their motivation and usage frequency of this technology. Therefore, algorithm literacy directly influences users' perception of the extent to which intelligent chatbots enhance information retrieval and service efficiency, potentially promoting their broader adoption.

Accordingly, this study proposes the following hypotheses:

H4c: Users with higher levels of algorithm knowledge and skills will perceive higher efficiency associated with library intelligent chatbots;

H5c: Users with higher levels of algorithm awareness will perceive higher efficiency associated with library intelligent chatbots;

H6c: Users with higher levels of critical thinking abilities will perceive higher efficiency associated with library intelligent chatbots;

H7c: Users with higher levels of algorithm social norms will perceive higher efficiency associated with library intelligent chatbots.

Research methodology and design

Mixed research methods enable both quantitative analyses to understand the effects between constructs and qualitative analysis to grasp the contextual conditions and details of variable interactions (Harrison and Reilly, 2011). This study conducts an exploratory investigation into how algorithm literacy influences attitudes toward using library intelligent chatbots. It employs a mixed research method, primarily using questionnaire surveys supplemented with semi-structured interviews. Convergent design is a type of mixed research method. This study draws on this paradigm to collect qualitative and quantitative results, continuously converging, interpreting, and refining the research findings from both group and individual perspectives. Specifically, Quantitative research validates the influence paths between variables using TAM. Qualitative research captures contextual details of users' technology acceptance processes.

This study focuses on library intelligent chatbots. These chatbots are an important part of library digital transformation. They use AI technology to provide users with instant, personalized information services. They typically offer functions such as: resource retrieval and recommendation, frequently asked questions answering, and borrowing management assistance. Figure 2 shows the intelligent chatbot interface of Shaanxi Normal University Library. On the left side, there are two tabs: "Common Questions" and "Self-service". Under "Common Questions", several subcategories appear as clickable buttons, such as "Electronic Resource Classification", "Circulation Reading Service", and others. Below these buttons, a list of frequently asked questions is provided. The right side demonstrates the interactive solution. A user asks, "Where can I find the database of modern newspapers purchased by the school?" The intelligent robot responds with a detailed thinking process. It mentions checking the database introduction. Finally, it provides the user with the address of the needed database.

Questionnaire survey. To ensure the reliability and validity of variables, measurement items are developed using an adaptive approach. We selected validated scales from existing literature and made context adjustments for library intelligent chatbots (Table 1). The questionnaire comprises 39 items (See Table 3 for the study's instrument). All variables are measured using a five-point Likert scale. During the scale development process, we invited two experts from the Library and Information Science field to review our initially adapted scales. These experts have over 8 years of experience in library information systems research and provided professional assessment of the content validity and applicability of the scales.

The survey was pre-tested with 30 library chatbots users from August 20th to 22nd, 2023. Based on the pre-test feedback, we made several adjustments to enhance the questionnaire's comprehensibility. These included terminology optimization (e.g., changing "algorithms have opacity and low explainability" to "algorithms have opacity and explainability, which makes me feel anxious") and structural adjustments to improve logical coherence. After these modifications, the experts reviewed the questionnaire again to ensure its scientific rigor and comprehensibility.

The questionnaire targeted active library service users including undergraduate/graduate students, faculty members, and personnel from research institutions with algorithm experience (Table 2). Most participants were between 18 and 32 years old. University students represented the highest proportion. The higher percentage of females in our sample is consistent with existing research findings. Several studies have shown that female users generally exhibit higher frequency in using library

Fig. 2 Interface of Shaanxi Normal University Library's Intelligent Chatbot.

Table 1 Reference sources for observed variables in questionnaire design.

Construct	Reference sources
Algorithm Literacy	(Deng et al., 2023)
Perceived Risk	(Meuter et al., 2005)
Perceived Distrust	(Liu et al., 2021)
Perceived efficiency	(Ongena et al., 2020)
Attitudes towards the Usage of Library Intelligent Chatbots	(DeLone and McLean, 2003)

Table 2 Sample structure.

Characteristics	Number	Percentage (%)
Gender		
Male	75	31
Female	164	69
Age		
<18	3	1
18–22	103	43
23–27	90	38
28–32	33	14
Above 33	10	4
Highest Education (Enrolled)		
Junior College and below	13	5
Undergraduate	152	64
Master's Degree	69	29
Doctoral Degree	5	2
Engaged in Algorithm Profession		
Yes	42	18
No	197	82

information services compared to male users (Applegate, 2008; Halder et al., 2010). This reflects the characteristics of academic library readership, which is dominated by young readers and student readers. These survey participants were recruited through social media platforms (campus platforms, professional communities, etc.). Before completing the survey, participants were shown an introduction to library intelligent chatbots. They also viewed the interaction process between users and these chatbots. Experience links were provided to ensure they had sufficient understanding of the technology. The final version of the questionnaire was distributed online through social media from September 5 to October 10, 2023. We received 281 responses. After removing incomplete and invalid responses, 239 valid submissions remained. This sample size exceeds six times the number of measured items (Zeng et al., 2009), meeting the requirements for PLS-SEM analysis.

Semi-structured interview. Unlike the random sampling used in the quantitative research, the semi-structured interviews employed purposive sampling, deliberately selecting representative interviewees. The interviewees mainly consist of users experienced with library intelligent chatbots usage, with a total of 8 participants, including 4 males and 4 females. The participants include university students and working professionals. The student group consists of 2 undergraduates and 4 graduate students. They come from computer science, library science, and communication majors. The professional group includes 2 individuals working in research institutions. Their ages range from 20 to 32 years. All participants have algorithm experience, varying from basic to advanced levels. Their usage frequency ranged from occasional consultation to regular interaction for research assistance. A semi-structured interview guide was developed based on research hypotheses and observed variables. The interviews were conducted online from August 26–29, 2023, and a total of 8 interview transcripts were collected and transcribed for research analysis (subsequently referred to as I1 to I8 representing the 8 interviewees).

Common method bias and multicollinearity test. Common method bias can lead to incorrect judgments about the adequacy of scale reliability and convergence effectiveness (Jordan and Troth, 2020). Therefore, this study used SPSS to conduct Harmon's single-factor test on the scale. The results extracted 6 factors with characteristic roots greater than 1, and the variance contribution rate of the first common factor was 39.26%, which did not exceed 40%, indicating that this study does not suffer from severe common method bias issues. Additionally, the variance inflation factor (VIF) was used to test for multicollinearity. The results showing VIF values ranging from 1.000 to 3.23, below the threshold of 3.3, indicating no serious multicollinearity issues in the data.

Table 3 Results for confirmatory factors analysis.

Construct	Items	Factor loading	Al-pha	AVE	CR
AK	AK1: I understand what algorithms are.	0.789	0.932	0.748	0.947
	AK2: I have knowledge of the principles and basic concepts related to algorithms.	0.897			
	AK3: I understand the types and characteristics of algorithms.	0.904			
	AK4: I am familiar with the applications and purposes of algorithms.	0.799			
	AK5: I am knowledgeable about the usage methods and strategies of different algorithms.	0.894			
	AK6: I am proficient in devising strategies and solving problems using algorithms.	0.897			
AA	AA1: I can be aware of the existence of algorithms.	0.738	0.830	0.663	0.887
	AA2: I know whether the system uses algorithms or not.	0.847			
	AA3: I can understand that the mechanism and output results of algorithm models may be inaccurate.	0.835			
	AA4: I can understand and assess the reliability of the mechanism and output results of algorithm models.	0.832			
CT	CT1: Before using algorithms, I can make reasonable judgments to differentiate between different algorithms.	0.798	0.923	0.651	0.937
	CT2: Before using algorithms, I can make a reasonable choice of algorithms to suit the current situation.	0.804			
	CT3: I understand the relationship between algorithms and data.	0.808			
	CT4: I can critically evaluate or question the reliability of the data input to algorithms.	0.816			
	CT5: I can understand the limitations of algorithm models in the current problem context.	0.824			
	CT6: I can assess and evaluate the limitations of algorithm models in the current problem context.	0.823			
	CT7: I can evaluate whether algorithm outputs are reasonable and accurate.	0.791			
	CT8: I can use algorithms rationally and critically to assist personal decision-making.	0.790			
ASN	ASN1: I can grasp the basic ethical and moral standards related to algorithms.	0.795	0.800	0.625	0.870
	ASN2: I can use algorithms in my work and studies in a disciplined manner.	0.802			
	ASN3: I can question whether the design and use of algorithms comply with technical ethics and social morals.	0.771			
	ASN4: When facing issues such as algorithmic discrimination or other algorithm-related infringements, I can use legal means to defend my rights.	0.794			
PR	PR1: Algorithms follow specific operational logic, appear sluggish, and cannot truly understand my needs.	0.872	0.884	0.740	0.919
	PR2: Algorithms may gather users' personal information and privacy during operation, exposing me on the internet.	0.886			
	PR3: Algorithms possess opacity and lack explainability, causing me to feel anxious.	0.801			
	PR4: Algorithm designs have unavoidable deficiencies or shortcomings, leading to a negative user experience.	0.879			
PD	PD1: Library intelligent chatbots can never match a professional counselor.	0.897	0.857	0.774	0.911
	PD2: With their extensive experience, counselors can provide me with more information.	0.857			
	PD3: Library counselors understand my needs better than intelligent chatbots.	0.886			
PE	PE1: I feel more comfortable when I receive faster results, even if they come from a computer.	0.833	0.771	0.686	0.867
	PE2: Using a library's intelligent chatbot can reduce waiting times in queues.	0.808			
	PE3: The library's intelligent chatbot can replace administrators in certain aspects.	0.843			
UA	UA1: I am willing to use the library intelligent chatbots.	0.799	0.804	0.628	0.871
	UA2: I will consider the advice provided by the library intelligent chatbots.	0.761			
	UA3: I will continue to use the library intelligent chatbots.	0.783			
	UA4: The experience of using the library intelligent chatbots is pleasant.	0.824			

Reliability and validity of the instrument. This study conducted validity and reliability tests on the model using SmartPLS (Table 3). The estimated SRMR value of the model is 0.064, which is less than the standard of 0.08, indicating good model fit and acceptable adequacy. Alpha values for each variable range from 0.771 to 0.932, all greater than 0.7, indicating good internal consistency of the variables and high questionnaire reliability.

In terms of convergent validity, the standardized factor loadings of all observed variables are greater than 0.7, the composite reliabilities (CR) of all latent variables are greater than 0.7, and the average variance extracted (AVE) is higher than 0.5, meeting the requirements for convergent validity. The Fornell-Larcker criterion is used to test discriminant validity (Table 4). The results show that the square roots of the AVE for all latent variables are greater than the correlations with other latent variables, indicating good discriminant validity of the measurement model.

Data analysis and research findings

Quantitative analysis results. The results of the direct path analysis reveal that users' AK and skills reduce PR ($\beta = -0.366$, $P < 0.01$) and distrust ($\beta = -0.302$, $P < 0.05$). Thus, H4a and H4b are supported. Users' AA enhances PE ($\beta = 0.300$, $P < 0.01$). Thus, H5c is supported. ASN significantly positively influence PE ($\beta = 0.223$, $P < 0.01$). Thus, H7c is supported. Additionally, PR decreases user attitudes towards using library chatbots ($\beta = -0.262$, $P < 0.01$), while PE enhances them ($\beta = 0.550$, $P < 0.001$). Thus, sH1 and H3 are supported. However, PD does not significantly negatively affect attitudes towards use. Thus, H2 is not supported.

Overall, the model explains 33.8% of PR variance, 26.1% of PD variance, 35.1% of PE variance, and 38.7% of library chatbots usage attitude variance (Fig. 3).

The findings reveal important mediation effects. Algorithm literacy in various domains has indirect impacts on library

Table 4 Discriminant Validity of Constructs (Fornell-Larcker).

	AK	AA	CT	ASN	PR	PD	PE	UB
AK	0.865							
AA	0.720	0.814						
CT	0.770	0.745	0.807					
ASN	0.590	0.689	0.647	0.791				
PR	−0.408	−0.267	−0.299	−0.182	0.860			
PD	−0.210	−0.210	−0.289	−0.148	0.752	0.880		
PE	0.484	0.552	0.477	0.510	−0.183	−0.148	0.828	
UB	0.430	0.469	0.471	0.553	−0.301	−0.212	0.581	0.792

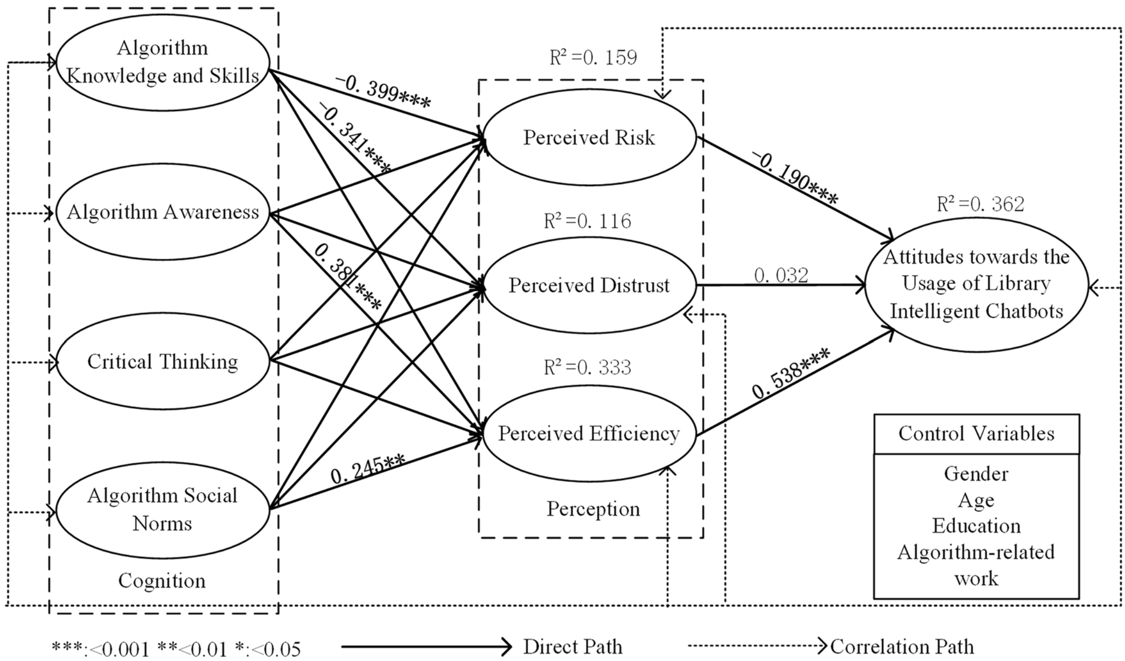

Fig. 3 Research Model Results.

Table 5 Mediation Path Analysis.

Path	Direct Effect	Indirect Effect		
		By PR	By PE	By PD
AK→UA	0.0779^{b}(0.0070, 0.1488)	0.0402^{b}(0.0038, 0.0824)	0.1313^{b}(0.0836, 0.1862)	−0.0085(-0.0442, 0.0247)
AA→UA	0.1220^{b}(0.0369, 0.2072)	0.0329^{b}(0.0042, 0.0744)	0.1690^{b}(0.1061, 0.2391)	−0.0043(-0.0322, 0.0200)
CT→UA	0.1445^{b}(0.0679, 0.2210)	0.0356^{b}(0.0059, 0.0772)	0.1362^{b}(0.0812, 0.1988)	−0.0111(-0.0427, 0.0208)
ASN→UĀUA	0.2668(0.1760, 0.3575)	0.0267^{b}(0.001, 0.0669)	0.1543^{b}(0.0894, 0.2246)	−0.0042(-0.0283, 0.0169)

"b" indicates statistically significant effects. And the 95% Confidence Interval is usually indicated in parentheses.

chatbot usage attitudes. These impacts occur through PR and efficiency. There was no significant indirect effect of algorithm literacy on library chatbots attitudes via PD towards the chatbots (Table 5).

The results indicate the influence of control variables on each variable (Table 6). Age correlates positively with AK and skills ($\beta = 0.315$, $P < 0.001$), AA ($\beta = 0.199$, $P < 0.05$), and CT ($\beta = 0.271$, $P < 0.001$), while negatively correlating with PR ($\beta = -0.406$, $P < 0.001$) and PD ($\beta = -0.345$, $P < 0.001$). However, gender did not significantly affect any of the variables.

Using non-algorithm-related workers as the reference group, those in algorithm-related occupations exhibited higher levels of algorithm literacy, including AK and skills ($\beta = -0.331$, $P < 0.001$), AA ($\beta = -0.198$, $P < 0.001$), CT ($\beta = -0.221$, $P < 0.001$), and ASN ($\beta = -0.187$, $P < 0.001$).

Qualitative analysis results. According to the requirements of convergent design paradigm, further qualitative analysis is needed to explore more detailed and in-depth findings. Therefore, this study starts from both cognitive and perceptual perspectives. It further understands the interaction between algorithm literacy and the usage attitude of library intelligent chatbots. This enriches the understanding of how algorithm literacy influences the usage attitude towards library intelligent chatbots.

Table 6 The influence of control variables on each variable.

	AK	AA	CT	ASN	PR	PD	PE	UA
Gender	−0.090	−0.073	−0.045	−0.069	0.006	−0.039	0.031	0.064
Age	0.315[b]	0.199[b]	0.271[b]	0.140	−0.406[b]	−0.345[b]	0.135	−0.057
Education	−0.049	−0.031	−0.050	−0.010	0.218[b]	0.208[b]	0.052	−0.026
Algorithm-related work	−0.331[b]	−0.198[b]	−0.221[b]	−0.187[b]	−0.113	−0.108	0.008	−0.046

"b" indicates statistically significant effects.

Theme 1: Algorithmic Literacy Serves as the Key Cognitive Foundation for Users to Evaluate and Accept Library Intelligent Chatbots.

Algorithm Knowledge and Skills: Users focus on chatbot operational mechanics and programming. *"I care about how the algorithm works behind it, which determines whether I trust it* (I1)." *"After understanding its basic working principles, my concerns decreased significantly* (I3)".

AlgorithmAwareness: Most users have a first impression of algorithms as quick and convenient. *"When I first used it, I felt it was very convenient, no need to queue for human service* (I4)." *"It responds to my questions immediately. this instantaneity was what I noticed first* (I7)".

Critical Thinking: Users believe dialectical thinking encourages self-reflection and rational usage attitudes. *"I consider whether its answers are reasonable rather than blindly accepting them* (I2)".

Algorithm Social Norms: Users' awareness of algorithmic social norms affects their expectations and satisfaction. *"Those unfamiliar with AI ethical norms often have unrealistic expectations of chatbots, leading to dissatisfaction when these expectations aren't met* (I5)."

Theme 2: Efficiency Advantages Outweigh Trust Deficits.

Perceived distrust: All interviewees expressed higher trust in human services, especially for handling complex issues. *"For complex research questions, I still trust professional librarians more* (I3)." However, despite this distrust, users still choose to use chatbots. *"While I don't fully trust its answers, it's sufficient for basic queries* (I2)." Social factors also influence this choice. *"Sometimes I don't want to interact with people. Asking questions through a chatbot feels more comfortable* (I7)." Time efficiency is also an important consideration. *"Waiting for librarian responses is sometimes too slow* (I8)".

Perceived efficiency: Time and space flexibility are highly valued. *"It can search the entire database in seconds, a speed human can't match* (I1)." Users also appreciate the guidance function. *"I like how it guides me to narrow down my search step by step, which is much more efficient than figuring it out myself* (I4)." *"Not having to worry about library closing times and getting help anytime is important for my research progress* (I6)".

Theme 3: User Risk Assessment is Based on Multiple Dimensions Rather Than Single Technical Characteristics.

Concerning PR, users consider multiple factors in their assessment. Interface design affects trust. *"If the interface looks professional, I feel safer* (I8)." Privacy issues are common concerns. *"I worry it might record my search history, which raises privacy concerns* (I2)." Functional performance also influences risk assessment. *"When it accurately answers my specialized questions, my risk assessment decreases* (I4)." Institutional endorsement increases credibility. *"I check whether the school officially recommends using this system, which affects my judgment of its safety* (I5)".

Discussion and recommendations

This study investigated the influence mechanism of algorithm literacy on users' attitudes towards using library intelligent chatbots. It finds that algorithmic literacy has a positive effect on library intelligent chatbots acceptance. Based on this, gender, age, educational level, and algorithm-related work are defined as control variables to explore their impact on various variables. The main conclusions are as follows:

In the process of users interacting with library intelligent chatbots, their cognitive level significantly impacts factors such as PR, PE, and PD. The quantitative analysis results show that users' AK and skills significantly reduce the degree of PR and PD, while AA significantly improves PE. This means that users with higher cognitive levels and more knowledge and skills related to algorithms have relatively higher trust in intelligent chatbots and perceive lower risks. Additionally, ASN positively influence users' PE of library intelligent chatbots. Interview data also show that users believe ASN affect their perceptions of the limitations, practicality, and functional limits of chatbots, thereby influencing efficiency perception. This result confirms the view of Xia et al. (2023) that the level of algorithm literacy affects individuals' interactions with AI chatbots representing algorithms. Therefore, improving and enhancing algorithm literacy is important to improving the quality of user interactions with intelligent technology.

Users' attitudes towards using library intelligent chatbots are closely related to their perceived levels of risk and efficiency. The survey results indicate that users have a high demand for chatbots efficiency, including expectations for convenient, "24/7" service, and PE has a significant path coefficient in the attitude influence model. Users' PE of intelligent chatbots directly determines their acceptance (Yi-No Kang et al., 2023). Simultaneously, user experience uncertainties are also considered, including PRs regarding service performance and data security. These PRs negatively impact usage attitudes, consistent with PR influence studies in other fields like online healthcare (Wang et al., 2023b). Users' core expectation of library intelligent chatbots is to quickly and accurately obtain answers to their questions. This reflecting a preference for chatbots services that provide precise, comprehensive, and rapid responses.

Trust plays a key role in adopting AI-driven educational technology for learning (Nazaretsky et al., 2025). However, our research reveals users' PD does not significantly impact their usage attitudes. This finding contrasts with some existing literature. It suggests that in specific contexts, other factors may be more important than distrust. Qualitative research results reveal that users want to explore new technology. This curiosity-driven behavior may offset the negative effects of distrust. Secondly, chatbots offer a way to get library services without social pressure. This benefit may be more important to them than their distrust of the technology. Finally, the efficiency of chatbots is a key factor. Users value the quick and convenient service. When they see that chatbots can solve their problems quickly, this advantage may reduce the impact of distrust on their attitude toward using the technology.

The study shows that algorithm literacy affects user attitudes through the mediating variables of PE and PR Users with higher algorithm literacy tend to hold more positive attitudes toward intelligent chatbots. This finding aligns with the research of Shin et al. (2022), where users with higher algorithm literacy, due to their deeper understanding and recognition of algorithms. They recognize the potential and benefits of algorithms more clearly. As a result, they are more likely to actively choose algorithmic systems to solve problems and enhance efficiency Users engaged in algorithm work also find the chatbot's data rich and concise, and prefer the chatbots (I8). These results indicate a significant association between algorithm literacy and technology acceptance/use. They provide a foundation for future research to further explore and validate the impact of algorithm literacy. Additionally, the mixed research results of this study indicate that the impact of perceived factors on user attitudes varies based on cognitive factors. This finding aligns with the core argument of the TAM. The attitude of individuals or organizations towards new technology is determined by their evaluation of different perceived factors (Venkatesh et al., 2003).

Algorithm literacy is related to demographic characteristics such as individual age and experience in algorithm-related work. This conclusion aligns with the view of Trepte et al. (2015) that an individual's literacy is closely related to their demographic attributes, cognitive factors, and even motivational factors. Quantitative research results reveal that age is positively correlated with algorithm literacy, which contrasts with the findings of Dogruel et al. (2022). The discrepancy may stem from differences in sample age structure. This study's sample mainly focuses on the 18-32 age range, possibly reflecting that within this specific age range, algorithm literacy increases with age. Future research should consider expanding the sample range to further explore the relationship between algorithm literacy and age. Meanwhile, individuals engaged in algorithm-related work exhibit higher algorithm literacy and tend to have a more positive attitude towards library intelligent chatbots. Users with an algorithm background usually have a deeper understanding of algorithms and superior programming skills This enables them to more comprehensively recognize the advantages and limitations of intelligent chatbots. Therefore, individuals with an algorithm background are more likely to endorse the application of intelligent chatbots and use their services more effectively.

Additionally, the results of this study show that individual algorithm literacy does not have a significant correlation with gender and education level. This partially contradicts the findings of Dogruel et al. (2022), where AK and awareness dimensions were found to be significantly positively correlated with individual education level. The reason may lie in that the improvement of individual algorithm literacy is not solely influenced by education level. And practical experience accumulation also plays a crucial role. Simultaneously, even individuals with higher education levels may have limited algorithm literacy if their research or work fields are not directly related to algorithms. Therefore, in educational practices aimed at improving individual algorithm literacy, personal backgrounds and actual abilities should be fully considered. Personalized training methods should be employed to make the training more specific and effective.

Research implications

This study has several theoretical and practical implications for the digitalization of academic libraries. Theoretically, this study integrates algorithmic literacy with the traditional TAM. It expands TAM's explanatory scope. Our research shows that in AI technology environments, users' algorithmic literacy serves as a cognitive resource. It significantly influences their acceptance willingness. This finding echoes discussions about how user knowledge affects technology acceptance. It especially builds on research that positions algorithmic literacy as a predictor of user interaction with algorithmic systems (Gagrcin et al., 2024). This broadens its application in AI research. Our study also challenges the one-dimensional understanding of algorithmic literacy in previous literature. It enriches the knowledge foundation of algorithmic literacy in user information behavior research. Existing studies emphasize the protective role of algorithmic literacy. For example, Obreja (2024) noted that users can use algorithmic literacy to counter controversial content on short video platforms. Noguera-Vivo and Grandío-Pérez (2025) highlighted the importance of algorithmic literacy in responsible news consumption by citizens. In contrast, our research shows that algorithmic literacy is not just a defense mechanism. It is also an empowering factor that promotes user acceptance of beneficial technologies. This provides a more diverse perspective for understanding user relationships with algorithmic technologies.

Additionally, our study reveals specific pathways through which algorithmic literacy influences technology acceptance. Through empirical analysis, we find that algorithmic literacy affects user acceptance attitudes by reducing PR and increasing PE. This provides a more detailed explanatory framework for understanding how algorithmic literacy works.

In practice, it is recommended that libraries, robot system developers, and users jointly work to improve users' algorithm literacy. This effort will enhance users' acceptance of library chatbots. At the library level, libraries can collaborate with platform developers. They can organize educational activities and online courses. These initiatives aim to help users build an AK framework and deepen users' understanding of the social norms of algorithm application. At the chatbots system designer level, focus on algorithm transparency and user guidance. These efforts are aimed at enhancing users' trust and understanding of the technology and increase their willingness to use it. At the individual user level, users should actively learn about algorithm-related knowledge to improve their problem-solving abilities and efficiency in intelligent systems. In this process, users' information literacy and digital skills are enhanced (Adetayo and Oyeniyi, 2023; Houston and Corrado, 2023).

Developers should prioritize the iterative upgrading of library intelligent chatbots system functions. This focus ensures the chatbots can respond to user queries more accurately and quickly, providing a personalized user experience. Additionally, service content should be regularly updated based on user feedback and interaction data to ensure services closely align with user needs. Finally, relevant stakeholders should focus on technical means and management strategies to protect user privacy data security effectively. For developers, clear user privacy protection policies and agreements should be established. This should manage the storage and retention period of user data in compliance. User personal information and conversation data should be anonymized and encrypted. For libraries, transparent information on data processing methods should be provided to users. They should actively address users' privacy concerns to build trust in intelligent chatbots services.

Limitations

There are still shortcomings in this study. Firstly, this study treats the attitude towards using library AI chatbots as the dependent variable. However, individuals may not necessarily act according to their attitudes, known as the attitude-behavior gap (Stieglitz et al., 2023). Therefore, future research could expand the study variables from attitudes to intentions and continued usage behaviors. Secondly, demographic variables such as gender, age, education level, and experience in algorithm work are considered as control variables in this study. Future studies could treat these variables as independent variables to further explore their effects on user attitudes at different stages. Lastly, this study used a sample of university students. This may limit how our results apply to other reader groups. Future research should use more diverse samples.

Data availability

The data are available at (https://doi.org/10.17632/6x36m9cd7f.1) and can also be obtained from the corresponding author, HL, upon request.

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Author contributions
Heng Lu: Supervision, Writing—review and editing. Xin Li: Investigation, Formal analysis, Writing—original draft.

Competing interests
The authors declare no competing interests.

Ethical statements
The study was approved by the Experimental Ethics Committee of the School of Journalism and Communication, Shaanxi Normal University (Approval No.: 002). The Committee reviewed the project on 10 August 2023, and the approved period for data collection was 15–30 August 2023. The research was conducted in accordance with relevant institutional guidelines and the principles of the Declaration of Helsinki. A scanned copy of the original Chinese approval letter has been submitted with this manuscript. An English translation has also been provided.

Informed consent
For the questionnaire, an electronic informed consent form is attached on the homepage of the survey platform. The form clearly explains the purpose of the survey, guarantees the anonymity of personal information, clarifies that the data will only be used for academic research (not for commercial purposes), and confirms that there are no potential risks of participation. Participants must read the entire consent form and click the "I agree" electronic button to proceed to the questionnaire—this operation is regarded as a valid expression of informed consent. The collection of questionnaire-based informed consent was conducted in two phases: the first phase was August 20, 2023 to August 25, 2023, and the second phase was September 5, 2023 to October 10, 2023. The second phase of data collection was approved by the Ethics Committee of the School of Journalism and Communication, Shaanxi Normal University through a supplementary approval (date: September 1, 2023). For the interviews, all participants are adults, and no vulnerable groups (e.g., patients, refugees) are involved. Given that all interviews were conducted online, written signature for informed consent was not feasible, so verbal consent was adopted instead. Prior to each interview, the researcher first read the standardized informed consent script (a copy of the script is provided) to the participant, and answered any questions raised. After confirming that the participant fully understood the purpose of the research, the scope of data use (including academic publication), and the recording arrangement, the researcher asked the participant to verbally confirm "I agree to participate" (the verbal consent process was recorded alongside the interview content for verification). The verbal informed consent for each participant was obtained on the same day as the interview, with the overall interview and consent collection period being August 26, 2023 to August 29, 2023.

Additional information
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