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The Influence Loop: How Perceived Norms Drive Academic Librarians' Use and Advocacy of Generative AI for Information-seeking

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ABSTRACT

Although generative AI tools are becoming increasingly popular in the workplace, owing partly to the belief that they can boost efficiency and productivity, empirical evidence is limited on the norms that drive actual usage and advocacy behaviour among academic librarians, particularly in developing countries. The current study aims to determine the influence of two types of perceived norms (injunctive norms and descriptive norms) on academic librarians' generative AI use and advocacy behaviours while examining the mediating role of behavioural intention and the role of digital information-seeking skills. This study applies the integrated behavioural model to correlational research among academic librarians in three Federal Universities in South-Western Nigeria. A sample of 133 participants was selected using simple random sampling, and responses were obtained using a self-report questionnaire. Partial Least Squares structural equation modelling validated the research model. Results suggest that injunctive norms and information-seeking skills directly influence Generative AI use and advocacy behaviours. Descriptive norms directly influence use behaviour, but not advocacy behaviour and behavioural intention mediates the relationship between injunctive norms and generative AI use behaviour. The Findings have implications for learning and technology adoption among library and information science practitioners, particularly for improving skills through targeted training programmes and social interaction in the workplace. The study offers insights into the potential of Generative AI for information discovery, advocacy, and service delivery by academic librarians in a non-Western context, and provides valuable evidence relevant to policymaking, training, and development.

Keywords: Generative artificial intelligence, higher education, information literacy, library services, skills, perceived norms

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INTRODUCTION

Information literacy constitutes individuals' personal, social, and ethical skills when interacting with information (Boon et al., 2007). It encompasses a wide range of knowledge, skills, and actual behaviours related to localisation, evaluation, and efficient use of information (Timmers & Glas, 2010). Within higher education, effective information literacy is necessary for critical thinking, information management, cross-disciplinary collaboration, and effective environmental adaptation among academic staff and students (Bhimani, 2011; Lauri & Virkus, 2019; White & Wood, 2021). Professional academic staff, like librarians, are mediators of information literacy as they are responsible for developing and teaching information literacy programmes for library users. Many librarians report that this makes their work more meaningful and highly engaging. It provides opportunities for collaboration with faculty while building a sense of community on and off campus (Tewell, 2018; Yevelson-Shorsher & Bronstein, 2018).

Effective information literacy begins with individuals seeing the need for information, gaining access to resources and developing skills for information-seeking (Bhimani, 2011). For centuries, libraries have been the primary location for achieving these. For instance, libraries provide reliable access to curated resources and expert assistance, and in many advanced countries, public libraries are essential locations for education and literacy (Sin & Kim, 2008; Whiteman et al., 2018). Librarians guide library users in the cognitive, investigative and ethical processes of information-seeking (Smith & Dailey, 2013). When public librarians in Demasson et al. (2019) were asked what information literacy entails, they stated that it requires an intellectual process and technical, social, and navigation skills to achieve desired results. This suggests that information-seeking among librarians is at the core of information literacy, as their job is a goal-oriented process that requires cognitive and practical skills and an adequate contextual understanding.

Despite their relevance to information discovery and delivery, librarians face challenges that limit the effectiveness of their practice. For instance, librarians are expected to follow professional norms and meet high client and institutional expectations ranging from the basic location of physical library resources to teaching critical information literacy and navigating many different complex technologies and web services (Tewell, 2018; Vitak et al., 2018); library staff often report having average levels of work engagement and high levels of workload imbalance (Martin, 2020); librarians who are in the process of becoming teachers lack pedagogical knowledge (Austin & Bhandol, 2013); and librarians whose promotion depends on research, complain that they lack time to conduct quality research (Donkor et al., 2024). In developing countries like Nigeria and South Africa, a substantial inadequacy in ICT knowledge and skills is evident among university librarians (Adeyoyin, 2005; Hoskins, 2005).

Separating information literacy from digital literacy in contemporary library service delivery is almost impossible. This is because of the recent breakthroughs in information discovery using generative artificial intelligence (Akakpo, 2024). Library staff in India express a positive attitude towards AI integration into library services, believing that it can enhance service delivery and that they are willing to understand its various uses and ethical implications (Kalbande et al., 2024a). Research indicates that Generative AI can help reduce library workers' workload by streamlining indexing and classification processes and extracting and composing descriptive metadata while enhancing consistency and accuracy (Formanek, 2024; Mahmud, 2024). AI-assisted chatbots can also facilitate personalised recommendations and specific support, and increase user satisfaction (Ikwuanusi et al., 2024).

Most importantly, generative AI offers tremendous opportunities for information retrieval (Y. Huang & J. Huang, 2024). This is particularly important for library staff dealing with clients' queries, whose work involves teaching and research or those interested in transitioning into teaching. A comprehensive list of generative AI tools useful for librarians can be found in (Gasparini & Kautonen 2023). The benefits of generative AI within libraries are not without costs. Research indicates that many academic libraries in the UK and China exclude AI integration from their strategic plans or agendas (Huang et al., 2023). For instance, AI integration and maintenance may be expensive for libraries, particularly in developing countries plagued with inefficient internet access, digitalisation policies and funding (Adarkwah et al., 2024; Kalbande et al., 2024b); issues relating to privacy infringement, security and inequality in access to digital resources may impede AI integration (Kalbande et al., 2024b; Zeb et al., 2024); and as prevalent with new technology adoption, inadequate technical skills and training of library staff (Adeyoyin, 2005; Akakpo, 2024; Hoskins, 2005). However, as new technologies evolve, they generally become cheaper, more accessible, and more secure while policies guiding their ethical use are developed. Hence, to help library staff adapt to emerging technologies in information seeking, it is crucial to understand their current norms, intentions, usage behaviour, and advocacy.

Investigating the norms, skills, and intentions that drive generative AI use and advocacy behaviour for information seeking is expedient for library and information science practitioners, as they are the principal mediators in its integration within academic libraries. Although generative AI tools are becoming increasingly popular in the workplace, owing partly to the belief that they can boost efficiency and productivity, empirical evidence is limited on the norms that drive actual usage and advocacy behaviour among academic librarians, particularly in developing countries where libraries have insufficient access to fiscal and infrastructural resources, and where digital information seeking skills are inadequate.

In addition, very little is known about how digital information-seeking skills influence generative AI use and advocacy behaviour among library and information science practitioners. Hence, this study hopes to bridge these gaps.

The current study aims to determine the influence of two types of perceived norms (descriptive norms and injunctive norms) on academic librarians' generative AI use behaviour and advocacy, while examining the mediating role of behavioural intention and the role of digital information-seeking skills. This study seeks to inform institutional adoption initiatives and guide policies for training and the ethical integration of generative AI for research and learning. Most importantly, it provides context-specific insights that identify constraints and enablers of AI integration within academic libraries.

Beyond examining generative AI uses among academic librarians, this study makes a theoretical contribution by refining the application of the Integrated Behavioural Model (IBM). While IBM recognises normative influence as a determinant of behaviour, prior technology adoption studies have often treated perceived norms as a single construct. By explicitly distinguishing between injunctive norms (perceived social approval) and descriptive norms (perceived behaviour of others) and examining their differential associations with both generative AI use and advocacy, this study extends IBM's explanatory scope. This refined application is particularly important within a non-Western academic library context, where professional norms and institutional expectations may shape technology-related behaviours in distinct ways.

LITERATURE REVIEW

Theoretical Framework and Hypothesis Development

Research in social psychology and consumer behaviour suggests that a significant influencer of individuals' behavioural intentions and actual behaviour is the perception of social pressure. Findings from empirical, review and theoretical literature indicate that social influence is essential in adopting new technology (Kavandi & Jaana, 2020; Teo & Noyes, 2014; Venkatesh et al., 2016). Given this, research on the impact of social influence in the context of technology adoption has been heavily reliant on the Unified Theory of Acceptance and Use of Technology (UTAUT and UTAUT 2) (Venkatesh et al., 2003, 2012), compared to the subjective norms in the foundational theories on which the UTAUT is based, e.g. the Theory of Reasoned Action (TRA) (Heilbroner et al., 1980) and the Theory of Planned Behaviour (TPB) (Ajzen, 1991), which have been useful in a variety of change interventions (Hardeman et al., 2005; Jemmott, 2012; Mosleh et al., 2014). Perhaps this is based on the belief that social influence transcends individual beliefs of the opinion of relevant referent individuals to actual recommendations and behaviour (Eckhardt et al., 2009).

However, recent developments in the TRA and TPB have incorporated elements from similar behavioural theories to create

the integrated behavioural model (IBM). As hypothesised in the TPB and TRA, intention is the most potent predictor of behaviour. However, a strong intention to take on behaviour may depend heavily on knowledge and skill, the absence of or limited environmental constraints, strong behavioural salience and significant experience that makes behaviour habitual (Montãno & Kasprzyk, 2015). In the TRA and TPB, Subjective norms refer to the perceived social expectation of an individual to engage or refrain from a particular behaviour (Ajzen, 1991). Within these frameworks, subjective norms are injunctive (i.e. normative beliefs about the expectation and approval of others). However, this may not entirely capture normative influences (Montãno & Kasprzyk, 2015). According to Fishbein & Ajzen (2010), the perceived behaviour of one's referent group (descriptive norms) is also a potent attribute of normative influences. Meta-analytical studies' findings suggest that descriptive norms have a medium to strong correlation with behavioural intention and can be effective in interventions targeted at behavioural change (Borsari & Carey, 2003; Rivis & Sheeran, 2003). The current study examines normative pressure to use Generative AI through the Integrated Behavioural Model (IBM). While IBM accommodates both injunctive and descriptive norms, prior technology adoption research has often operationalised normative influence as a general construct. By explicitly separating injunctive norms and descriptive norms and examining their differential associations with generative AI use and advocacy behaviours, this study refines the application of IBM in a professional technology adoption context. This distinction allows for a more nuanced understanding of normative influence, clarifying whether librarians' engagement with generative AI is driven primarily by perceived social approval or by observed effectiveness through colleagues' use. Given the explicit separation of injunctive and descriptive norms in IBM, we argue that the observed actual usage of generative AI by fellow librarians will influence usage intention, use behaviour, and advocacy. Therefore, we hypothesise that:

H1. Injunctive norm is positively associated with generative AI use behaviour among librarians.

H2. Descriptive norm is positively associated with generative AI advocacy behaviour.

H3. Injunctive norm is positively associated with generative AI advocacy behaviour.

H4. Descriptive norm is positively associated with generative AI use behaviour among librarians.

In addition to actual use, this study examines advocacy as a distinct behavioural outcome. While use behaviour reflects an individual's personal engagement with generative AI tools, advocacy involves actively recommending, endorsing, or promoting these tools to others. In the

context of academic librarianship, advocacy represents a meaningful extension of technology adoption because librarians function as information intermediaries, educators, and institutional actors whose professional recommendations can influence users' practices and institutional decision-making (Emanuel, 2013; Sun et al., 2011). As such, advocacy constitutes a socially oriented and professionally consequential behaviour that may be shaped by normative pressures in ways that differ from individual use.

A consensus in studies using the TRA, TPB, and IBM is that behavioural intention is the most significant predictor of behaviour (Fishbein & Ajzen, 2010; Montãno & Kasprzyk, 2015). The potency of intention is evident in a meta-analytical study on behavioural intention and behaviour change in experimental research, which found that a medium to a large change in intention is associated with a small to medium change in actual behaviour (Webb & Sheeran, 2006).

In technology adoption studies, intention not only gives a glance into users' adoption behaviour but can also offer insights into continued use and advocacy behaviour (Zhou & Ma, 2025). Indeed, various studies on generative AI use have limited their outcome variable to intention (Cao & Peng, 2024; Kim, 2025; Tang et al., 2025). At the same time, other studies maintained their role as a mediator (Ivanov et al., 2024; Zaim et al., 2024). According to Ajzen (2011), as time passes, more intervening events can influence the translation of intention into actual behaviour. However, experimental or correlational research can explore the intention-behaviour relationship. Therefore, we hypothesise that:

H5a. Intention will mediate the relationship between injunctive norms and generative AI use behaviour.

H5b. Intention will mediate the relationship between descriptive norms and generative AI use behaviour.

H6a. Intention will mediate the relationship between injunctive norms and generative AI advocacy behaviour.

H6b. Intention will mediate the relationship between descriptive norms and generative AI advocacy behaviour.

Many behaviours relating to technology adoption require adequate skills for effective performance (Goncalves et al., 2018). Digital skills are essential for effective search, retrieval, dissemination, and ethical use of information (Akakpo, 2024). According to Ajzen (2014), for a positive intention to translate into actual behaviour, individuals must have the means, skills, and other necessary resources to perform the behaviour. Among librarians, digital skills, when available, can aid the development and management of digital library resources and improve service delivery (Hamad et al., 2021; Nisar et al., 2024; Okeji et al., 2020), and when insufficient, it can hinder the integration of technological innovation (Hoskins, 2005). It can also determine the diffusion of ICTs and advocacy (Hamad et al., 2021; Rafi et al., 2019). A study on the

determinants of ICT adoption behaviour found digital skills to be a significant moderator of technology adoption (Yu et al., 2017). Therefore, we hypothesise:

H7. Digital information skill is positively associated with generative AI use behaviour among librarians.

H8. Digital information skills are positively associated with generative AI advocacy among librarians.

Figure 1 presents the conceptual framework guiding this study. The framework posits that perceived norms, operationalised as injunctive and descriptive norms, serve as key social predictors of academic librarians' engagement with generative AI (Fishbein & Ajzen, 2010; Montãno & Kasprzyk, 2015). These normative influences are proposed to affect both generative AI use behaviour and advocacy directly, while also shaping behavioural intention to use generative AI. Behavioural intention functions as a mediating mechanism through which normative pressures may translate into actual use and advocacy behaviours (Fishbein & Ajzen, 2010). In addition, digital information-seeking skills are conceptualised as a capability-based factor that directly supports both generative AI use and advocacy, reflecting the role of skills in enabling effective technology engagement (Ajzen, 2014; Yu et al., 2017). Together, the framework integrates social influence, intention, and skill-based resources to explain variation in generative AI use and advocacy among academic librarians.

MATERIALS AND METHODS

Participants and Procedures

This study employs a cross-sectional research design. A survey was conducted among academic librarians working in general and faculty libraries from 3 public universities in southwestern Nigeria: The Federal University of Technology, Akure,

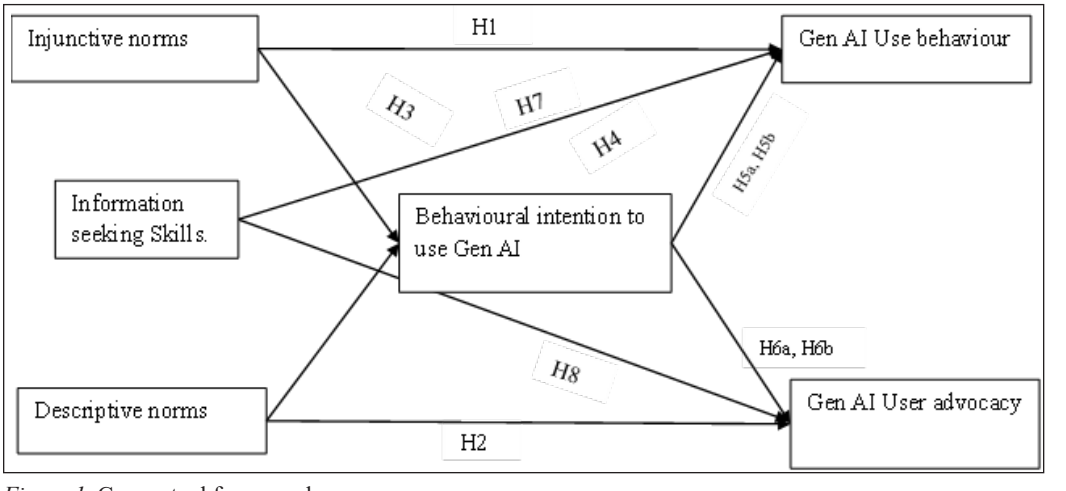

Figure 1. Conceptual framework

Ekiti State University and Federal University Oye. A simple random sampling technique was selected for this study because of its convenience and affordability benefits. Respondents were invited to participate in an online questionnaire through a Google Forms link. A descriptive analysis of the study samples is depicted in Table 1. Although the study draws on academic librarians from three public universities, the sample represents librarians within these specific institutional contexts rather than the entire population of academic librarians in Nigeria. Consequently, the findings should be interpreted as reflective of the sampled universities rather than broadly generalised across all academic library settings.

Respondents were predominantly male (54.9%) and aged 36 to 50 (52.2%). Most respondents (39.8%) have bachelor's degrees, and most respondents (57.5%) have worked as librarians for less than 10 years.

Questionnaire Design and Data Collection

A self-report questionnaire is instrumental in obtaining responses from the study participants. In addition to questions obtaining information on the demographic characteristics of the respondents, which solicits gender, age, level of education and number of years of librarianship experience information, the questionnaire also contained items from six major variables, namely.

1. Injunctive norms
2. Descriptive norms
3. Behavioural intention to use generative AI
4. Digital information-seeking skills
5. Generative AI use of behaviour
6. Generative AI user advocacy

Questions regarding injunctive and descriptive norms and intention to use

Table 1
Demographic characteristics of respondents

Variable	Frequency	Percentage (%)
Gender		
Male	62	54.9
Female	51	45.1
Age		
Below 35 years	13	11.5
36 to 50 years	59	52.2
Above 50 years	41	36.3
Level of education		
Diploma	38	33.6
Bachelor's degree	45	39.8
Master's degree	24	21.2
Doctorate	6	5.3
Years of librarianship experience		
Below 10 years	65	57.5
11 to 20 years	40	35.4
Above 20 years	8	7.1

generative AI were adapted from a prior study (Park & Smith, 2007) and phrased to fit the study's context appropriately. Sample items on injunctive norms are 'most people whose opinion I value would approve of my using Gen AI tools to search for information' and 'most people who are important to me would support that I use Gen AI tools to search for information'. Responses were obtained on a 7-point Likert-type scale ranging from 1 = 'Strongly Disagree' to 7 = 'Strongly Agree'. Sample items on descriptive norms are 'most people who are important to me use Gen AI tools to search for information' and 'most people whose opinions I value have used Gen AI tools to search for information'. Responses on descriptive norms were obtained on a 7-point Likert-type scale ranging from 1 = 'Strongly Disagree' to 7 = 'Strongly Agree'. Sample items on behavioural intention are 'I intend to use Gen AI tools to search for information in the near future' and 'I will use Gen AI tools to search for information in the near future'. Responses on behavioural intention were also obtained on a 7-point Likert-type scale ranging from 1 = 'Strongly Disagree' to 7 = 'Strongly Agree'.

Selected questions measuring generative AI use behaviour were adapted from the information-seeking behaviour scale designed by Timmers and Glas (2010) and rephrased to fit the study context. Respondents were asked to provide answers to the statement, 'When I search for information using generative AI tools. Sample items in the scale are 'I search for general background information of the topic' and 'I adjust the questions when I find little or no information on the topic'. Items on the information-seeking behaviour scale were measured on a 6-point Likert-type scale, with responses ranging from 1 = 'Strongly Disagree' to 6 = 'Strongly Agree'. Questions measuring generative AI advocacy were adapted from the e-WOM scale designed by Goyette. et al. (2010). Some examples are 'I speak of Gen AI tools more frequently than any other information-seeking tools' and 'I discuss the user-friendliness of Gen AI tools. Responses were obtained from participants on a 7-point Likert-type scale, ranging from 1 = 'Strongly Disagree' to 7 = 'Strongly Agree'. A modified online searching skills questionnaire, which was designed to assess respondents' online searching self-efficacy by Monoi et al. (2005), was used to measure the digital information-seeking skills of respondents in the study. Sample items are 'I can construct a complex search using more than one Boolean operator and grouping terms using parentheses' and 'I can narrow or broaden my search to retrieve the appropriate quantity of information'. Responses were obtained on a 6-point Likert-type scale ranging from 1 = Strongly Disagree to 6 = 'Strongly Agree'.

Preliminary Analysis

The dataset for this study was cleaned before data analysis to remove missing values and outliers. Descriptive data such as age, gender, level of education and number of years of librarianship experience were analysed using IBM SPSS version 24. However, the research hypothesis was

analysed using Smart PLS software version 4.1.1.1. A structural equation modelling comprising 5000 bootstrapping sub-samples was conducted. PLS-SEM was chosen for the study because it utilises multiple observed indicators to measure unobserved latent concepts. It also confirms and validates the constructs of an instrument and their relationships with other constructs(Chin, 1998; Hair et al., 2014). PLS-SEM is particularly relevant for the current study because it can ameliorate the inadequacies of studies conducted with small samples (Rigdon et al., 2017). Although PLS-SEM is appropriate for exploratory models and complex relationships, the results should be interpreted with an awareness of its emphasis on prediction rather than overall model fit, and its reliance on correlational data.

PLS-SEM is specifically designed to achieve greater statistical power with small sample sizes compared to covariance-based SEM. According to Hair et al. (2017), at least 100 samples are recommended for PLS-SEM models with multiple arrows pointing at endogenous variables, assuming medium effect sizes, 5% significant levels and 80% power. Considering that the current study has two endogenous variables each receiving four arrows, the sample size of 113 comfortably meets these guidelines, satisfying the Inverse Square Root requirement. G power analysis was instrumental in determining the minimum required sample size for the study. For studies with medium effect sizes (i.e., $f^2 = 0.15$) and a power of 0.80, the minimum sample size typically used in social science research is approximately 80-100 (Cohen, 1988).

RESULTS

Measurement Model

All constructs in the study were reflectively measured. According to Ringle et al. (2020), the reflective measurement model examines indicator reliability, convergent and discriminant validity, and internal consistency.

As table 2 depicts, the indicator loadings of all constructs exceeded the 0.5 significant threshold. Composite reliability scores for all constructs ranged from 0.78 to 0.89, and average variance extracted scores ranged from 0.50 to 0.63. Hence, all constructs in the study met the criterion for acceptable convergent validity. Results in table 2 also show that all the constructs in the model passed the reliability test, with Cronbach's alpha scores ranging from 0.62 to 0.85, suggesting that the constructs demonstrated medium to strong internal consistency.

To assess the discriminant validity of the study constructs, the Fornell and Larcker (1981) criterion and HTMT (Henseler et al., 2015) scores were evaluated. According to Fornell & Larcker's criterion, the assumption of discriminant validity is met when the AVE of each construct is greater than the squared correlation between a construct and any other construct in the model. Also, Henseler and colleagues posit that discriminant validity is achieved when the comparison of heterotrait and monotrait

Table 2
Construct validity and reliability.

Construct	Indicators	Factor loadings	VIF	Average Variance Extracted (AVE)	Rho_A	Composite Reliability (CR)	Cronbach's α
Descriptive Norms (DN)	DN1	0.838	1.411	0.575	0.681	0.797	0.623
	DN3	0.841	1.434				
	DN5	0.561	1.106				
Injunctive Norms (IN)	IN1	0.824	1.48	0.636	0.732	0.839	0.713
	IN3	0.848	1.534				
	IN5	0.714	1.281				
Behavioural Intention (BI)	BI1	0.888	1.798	0.514	0.84	0.798	0.712
	BI2	0.524	1.518				
	BI3	0.865	1.807				
	BI4	0.500	1.473				
Information Seeking Skills (ISS)	ISS1	0.742	1.513	0.501	0.834	0.857	0.808
	ISS11	0.681	2.096				
	ISS3	0.75	1.62				
	ISS5	0.677	1.543				
	ISS7	0.665	1.646				
	ISS9	0.728	2.343				
Generative AI use behaviour (ISB)	ISB1	0.761	1.808	0.538	0.864	0.89	0.857
	ISB11	0.783	2.137				
	ISB13	0.663	1.747				
	ISB3	0.736	1.874				
	ISB5	0.723	1.725				
	ISB7	0.768	1.827				
	ISB9	0.691	1.611				
Generative AI Advocacy Behaviour (GAIAB)	GAIAB1	0.763	1.522	0.524	0.707	0.814	0.70
	GAIAB3	0.79	1.431				
	GAIAB5	0.679	1.394				
	GAIAB7	0.654	1.187				

correlation ratios produces scores less than 0.85 or 0.9. The heterotrait correlation refers to cross-construct correlations, while the monotrait correlation refers to within-construct correlations (Rönkkö & Cho, 2022).

The results in Table 3 show that the assumptions of discriminant validity were not violated, as the AVE of each construct is greater than the squared correlation between other constructs, and HTMT values in the model were less than 0.9.

Structural Model

After confirming that the measurement model of PLS-SEM meets all relevant criteria, researchers can interpret the structural model, which involves running robustness checks to ensure the stability of results (Hair et al., 2019). These include examination of the coefficient of determination (R^2), Cross-validated redundancy (Q^2), Collinearity statistics, and the path coefficient for reflective measurements. The R^2 value for generative AI use behaviour (0.591) indicates the proportion of variance in information-seeking using generative AI that is associated with injunctive norms, descriptive norms, and digital information-seeking skills. In addition, generative AI advocacy behaviour produced an R^2 value of 0.372, indicating that the independent variables in the model are associated with 37.2% of the variance in generative AI advocacy behaviour. The R^2 value for behavioural intention (0.262) indicates that injunctive and descriptive norms are associated with 26.2% of the variance in behavioural intention.

The model's predictive power was evaluated using the cross-validated redundancy Q^2 values. This test omits a portion of the data matrix, approximates the model's parameters and predicts the omitted portion using the estimates that were previously computed (Ringle et al., 2020). According to Chin (1998), a model's predictive accuracy is sufficient when a high Q^2 value results from a small difference between the predicted and actual values. Hence, Q^2 values greater than 0, 0.25 and 0.50 demonstrate small, medium and large predictive relevance, respectively (Hair et al., 2019). The

Table 3
Discriminant validity of constructs

	Fornell-Lacker						HTMT				
Constructs	**1**	**2**	**3**	**4**	**5**	**6**	**1**	**2**	**3**	**4**	**5**
BI	0.717										
DN	0.435	0.758					0.586				
GAIAB	0.398	0.486	0.724				0.506	0.704			
IN	0.472	0.577	0.521	0.797			0.553	0.863	0.709		
ISB	0.59	0.594	0.505	0.659	0.733		0.655	0.784	0.618	0.833	
ISS	0.604	0.516	0.489	0.448	0.58	0.708	0.742	0.686	0.596	0.566	0.647

Q^2 values for behavioural intention, generative AI advocacy behaviour and generative AI use behaviour in the study's model were 0.22, 0.32 and 0.53, respectively. Therefore, behavioural intention demonstrates a small predictive power, generative AI advocacy behaviour demonstrates a medium predictive power, while generative AI use behaviour demonstrates a large predictive power. The assumptions of collinearity were not violated in the study's model, as VIF for all indicators was below three, based on Hair et al. (2019).

The results presented in Table 4 show that five of the six direct hypotheses proposed in the study were supported by statistically significant associations at the p = 0.05 significance level. Injunctive norm was significantly and positively associated with generative AI use behaviour (β = 0.35, t = 3.86, SD = 0.093, f^2 = 0.188, p = 0.000). Similarly, descriptive norm was significantly and positively associated with generative AI use behaviour (β = 0.19, t = 2.06, SD = 0.095, f^2 = 0.054, p = 0.039). Therefore, the findings confirmed H1 and H4.

The results also reveal that injunctive norm is significantly and positively associated with generative AI advocacy behaviour (β = 0.29, t = 2.47, SD = 0.119, f^2 = 0.082, p = 0.013). In contrast, descriptive norms were not significantly associated with generative AI advocacy behaviour (β = 0.175, t = 1.678, SD = 0.104, f^2 = 0.028, p = 0.093). Consequently, these findings confirmed H3 and rejected H2. Furthermore, digital information-seeking skills were significantly and positively associated with generative AI use behaviour (β = 0.18, t = 2.11, SD = 0.086, f^2 = 0.045, p = 0.035). Also, digital information-seeking skill was significantly and positively associated with generative AI advocacy behaviour (β = 0.245, t = 2.09, SD = 0.117, f^2 = 0.053, p = 0.035). Therefore, the findings confirmed hypotheses H7 and H8.

Regarding the effect size ($f2$), which measures a change in R2 with the omission of an exogenous construct, Cohen (1988), suggests that values of 0.02, 0.15 and 0.35 represent small, medium, and large effects, respectively. For generative AI use behaviour, the effect sizes for the exogenous constructs were injunctive norms ($f2$= 0.188), descriptive norms ($f2$= 0.054), and digital information seeking skills ($f2$= 0.045). For generative AI advocacy behaviour, the effect sizes were injunctive norms ($f2$ = 0.082), descriptive norms ($f2$ = 0.028), digital information seeking skills ($f2$= 0.053). The results show that injunctive norms have the strongest influence on both generative AI usage behaviour and advocacy behaviour. In contrast, descriptive norms have the least impact on advocacy behaviour. Additionally, it is important to note that the effects of digital information-seeking skills on both key constructs in this study are substantial.

Mediation Test of Behavioural Intention

The relationship between injunctive norms and generative AI use behaviour in the direct model was statistically significant, as shown in table 5. When behavioural

Table 4
Results of direct hypothesis testing

H	Constructs	β	STDEV	T	Sig	Conclusion
H4	DN -> GAIAB	0.175	0.104	1.678	0.093	Not Significant
H2	DN -> ISB	0.195	0.095	2.062	0.039	Significant
H3	IN -> GAIAB	0.293	0.119	2.473	0.013	Significant
H1	IN -> ISB	0.357	0.093	3.863	0.001	Significant
H8	ISS -> GAIAB	0.245	0.117	2.097	0.036	Significant
H7	ISS -> ISB	0.182	0.086	2.111	0.035	Significant

Table 5
Results of the indirect effects of behavioural intention

			95% CI Bootstrap BC		
Path	β	P values	LB	UB	Conclusion
DN -> BI -> GAIAB	0.009	0.762	-0.042	0.078	Not significant
DN -> BI -> ISB	0.055	0.1	0.009	0.154	Not significant
IN -> BI -> GAIAB	0.012	0.753	-0.054	0.097	Not significant
IN -> BI -> ISB	0.075	0.038	0.021	0.172	Significant

intention was included in the model, injunctive norm remained a significant predictor of generative AI use behaviour (β = 0.075, t = 2.079, p = 0.038). These results indicate that behavioural intention serves as a mediating variable in the association between injunctive norms and generative AI use behaviour. Accordingly, hypothesis H5a was supported.

In contrast, the results presented in Table 5 indicate that behavioural intention did not function as a mediating variable in the association between descriptive norms and generative AI use behaviour (β = 0.055, t = 1.643, p = 0.100), injunctive norms and generative AI advocacy behaviour (β = 0.012, t = 0.314, p = 0.753), and descriptive norms and generative AI advocacy behaviour (β = 0.009, t = 0.303, p = 0.762). Therefore, hypotheses H5b, H6a and H6b were not supported.

DISCUSSIONS

The study's primary objective was to examine the role of perceived norms and information-seeking skills on generative AI use and advocacy behaviours when behavioural intention is a mediator among academic librarians. The integrated behavioural model provided a sound foundation for explaining generative AI use and advocacy behaviours. The positive association between injunctive norms and both generative AI use and advocacy behaviours can be understood through the role of perceived social approval and professional expectations in shaping librarians' technology-related decisions, as emphasised in behavioural models of

normative influence (Fishbein & Ajzen, 2010; Montãno & Kasprzyk, 2015). Within academic library environments, librarians operate in close professional communities where peer expectations, managerial signals, and institutional culture strongly influence perceptions of acceptable and valued practices. When the use of generative AI is perceived as professionally endorsed or socially approved, librarians are more likely to align their behaviour with these expectations, not only by adopting the technology for their own information-seeking activities but also by supporting its broader diffusion, a pattern consistent with prior studies on social influence and technology adoption (Zino et al., 2022). Informal workplace interactions further reinforce this process by increasing awareness of colleagues' competencies and shared norms, thereby strengthening confidence in using emerging technologies (Cross et al., 2001). In addition, librarian-led generative AI training initiatives may function as visible institutional cues that legitimise generative AI use, reinforcing both individual engagement and professional endorsement of these tools within academic library settings (Carroll & Borycz, 2024).

The findings of this study also underscore the importance of contextualising the integrated behavioural model within a developing-country academic library setting. In contexts such as Nigeria, where institutional resources, formal AI policies, and infrastructural support may be uneven, social and professional norms can assume a more central role in shaping technology-related behaviours. Under such conditions, librarians may rely more heavily on peer expectations, professional approval, and shared workplace practices to guide decisions about engaging with emerging technologies. Prior research on emerging digital technologies in Nigeria, including frameworks for integrating metaverse technologies into educational contexts, highlights how institutional readiness, ethical considerations, and contextual constraints shape the adoption and use of advanced digital systems (Badiru & Aladelusi, 2023). This suggests that the influence pathways proposed in the integrated behavioural model may operate differently in non-Western professional environments, with normative pressures partially compensating for structural constraints (Fishbein & Ajzen, 2010; Montãno & Kasprzyk, 2015). By demonstrating how injunctive and descriptive norms function within this context, the study extends the applicability of IBM beyond predominantly Western settings and supports the need for context-sensitive interpretations of technology adoption models.

The association between descriptive norms and generative AI use behaviour can be explained by observational learning and social comparison processes within academic library settings, where individuals often look to peers for behavioural cues when engaging with new technologies (Miranda et al., 2024). When librarians observe colleagues using generative AI tools effectively, such behaviours provide practical cues about the utility, legitimacy,

and appropriateness of the technology for professional tasks. This form of learning helps reduce uncertainty surrounding emerging technologies and lowers perceived risk, thereby making individual experimentation more likely. Observing peers' successful use of generative AI may also normalise its integration into everyday information-seeking practices, encouraging wider uptake through shared professional routines (Miranda et al., 2024). Within academic libraries, these social learning processes can further promote collaboration, experimentation, and knowledge sharing, creating an organisational environment that supports the diffusion of generative AI tools (Gupta, 2025).

The association between injunctive norms and generative AI advocacy behaviour can be understood in relation to the evolving professional role of academic librarians and the expectations attached to that role. Prior research has shown that innovations in information technology have progressively expanded librarians' responsibilities beyond information provision to include instructional and educational functions, positioning them as key actors in promoting information literacy and responsible technology use (Sun et al., 2011). As teaching, learning, and research practices become increasingly technology-mediated, librarians' engagement with emerging tools is often evaluated against professional and institutional expectations. Within this context, perceived expectations from colleagues, supervisors, and the broader academic community can motivate librarians to move beyond personal use and actively endorse generative AI as part of their professional mandate. This normative pressure may be particularly salient among younger librarians, who may view advocacy for new technologies as a way of shaping professional identity, demonstrating competence, and contributing to the future direction of librarianship (Emanuel, 2013).

Advocacy represents a qualitatively different behavioural outcome from individual use, as it involves public endorsement, recommendation, and professional signalling rather than private engagement with technology. Within academic librarianship, advocacy is closely tied to professional identity and institutional responsibility, as librarians act as educators, information intermediaries, and trusted advisors whose recommendations can shape students' practices, faculty behaviour, and organisational adoption decisions (Emanuel, 2013; Sun et al., 2011). Because advocacy is outward-facing and professionally visible, it carries greater reputational and normative risk than individual use, making it more sensitive to perceived social approval and professional expectations. In this sense, librarians may be willing to experiment with generative AI based on observation alone, while advocacy requires stronger normative alignment and institutional legitimacy. This distinction helps explain why injunctive norms play a more prominent role in motivating advocacy behaviours, whereas descriptive norms may be sufficient to encourage individual experimentation and use (Zino et al., 2022).

The association between digital information-seeking skills and generative AI use behaviour can be explained by the role of skills in reducing cognitive and technical barriers to engaging with emerging technologies. Librarians with stronger digital competencies are better equipped to evaluate, experiment with, and integrate new tools into their information-seeking workflows, which increases confidence and lowers perceived difficulty when adopting generative AI. Prior studies indicate that digital information skills support effective search, retrieval, and ethical use of information technologies, thereby facilitating engagement with novel digital systems (Bolasco, 2023). This relationship is further reflected in evidence that library and information science students draw on existing information retrieval, summarisation, and analytical skills when incorporating AI tools into academic and professional tasks (Hossain et al., 2025). In this sense, digital information-seeking skills function as enabling resources that make the transition from traditional information practices to generative AI use more attainable within academic library contexts (Kalbande et al., 2024a).

The association between digital information-seeking skills and generative AI advocacy behaviour can be understood through the link between competence, credibility, and professional influence within academic libraries. Prior research has shown that librarians with strong digital competencies are often positioned as trusted experts in ethical information practices and technology governance, which enhances their professional credibility within institutions (Michalak, 2023). As a result, such librarians are more likely to feel confident in evaluating the benefits, limitations, and ethical implications of generative AI tools, increasing their willingness to publicly recommend or support their adoption. In organisational settings, employees with specialised skills frequently exert greater influence over technology-related decisions, particularly in contexts where managerial expertise in emerging technologies is limited, and leadership relies on expert input to navigate innovation and risk (Daft, 2017). In this way, digital information-seeking skills enable librarians not only to use generative AI effectively but also to assume advocacy roles grounded in expertise and institutional trust.

The mediating role of behavioural intention highlights the psychological process through which normative pressures are translated into generative AI use among academic librarians. Behavioural intention reflects a deliberate readiness to act, shaped by perceived social approval and professional expectations, and serves as a proximal driver of actual behaviour (Fishbein & Ajzen, 2010). When injunctive norms signal that generative AI use is professionally valued or expected, librarians are more likely to form strong intentions to integrate such tools into their information-seeking practices. Prior research suggests that intention plays a central role in converting social influence into technology adoption, particularly in

professional contexts where norms function as intrinsic motivators (Nassar et al., 2019). This mechanism may be especially salient in academic libraries, where professional norms can at times outweigh formal managerial directives, reinforcing the role of intention as a bridge between social expectations and technology use (Fang et al., 2025; Venkatesh et al., 2012).

CONCLUSION

This study demonstrates that the integrated behavioural model provides a robust framework for understanding generative AI use and advocacy among academic librarians when normative influences, intention, and skill-based capabilities are considered together. By distinguishing between injunctive and descriptive norms and examining their associations with both use and advocacy behaviours, the study extends the application of IBM to a professional technology adoption context within a developing-country academic library environment. The findings highlight how perceived social approval, observed peer behaviour, and digital information-seeking skills jointly shape librarians' engagement with generative AI, with behavioural intention serving as a key mechanism linking normative pressures to actual use. Beyond individual adoption, the study underscores advocacy as a distinct and professionally consequential outcome, reflecting librarians' roles as educators and institutional actors. Collectively, these insights advance understanding of how social, cognitive, and contextual factors interact to influence emerging technology adoption in academic libraries, particularly outside Western-centric research settings.

Theoretical Contributions

This study contributes to the literature in several important ways. First, it extends scholarship on generative AI adoption in library and information science by empirically examining both use and advocacy behaviours among academic librarians, an outcome combination that remains underexplored. Second, by distinguishing between injunctive and descriptive norms, the study refines the application of the integrated behavioural model, demonstrating that normative influences may operate differently depending on the nature of the behaviour under investigation. Specifically, injunctive norms appear more salient for behaviours involving persuasion, endorsement, and social approval, whereas descriptive norms may be more relevant for observable and collective practices. Third, the findings underscore the role of digital information-seeking skills as a capability-based enabler of both use and advocacy, highlighting how skills can reinforce normative influences and support organisational-level technology diffusion. Finally, the absence of a significant mediating role of behavioural intention in advocacy behaviour suggests that advocacy may be driven by additional motivational mechanisms beyond intention, pointing to the need for future theoretical extensions that incorporate factors such as trust, professional identity, or ethical orientation.

Practical implications of the study

The findings of this study also offer practical implications for academic and special libraries. First, the strong role of digital information-seeking skills in both generative AI use and advocacy suggests the need for continuous, targeted training programmes that focus not only on technical proficiency but also on ethical and responsible AI use in library services. Such training initiatives could include practical modules on information retrieval, content evaluation, bias awareness, and privacy protection when using generative AI tools.

Second, the limited role of descriptive norms in predicting advocacy behaviour indicates that mere exposure to colleagues' AI use may be insufficient to encourage active promotion of generative AI. To address this, library leadership and senior professionals can play a more visible role in legitimising ethical AI use by explicitly endorsing AI-related initiatives, supporting peer mentoring, and creating formal opportunities for knowledge sharing. Clear institutional signals of approval may therefore be critical in transforming individual experimentation into collective advocacy and sustained adoption.

Limitations and Directions for Future Research

Although the current study offers valuable insights into the application of the Integrated Behavioural Model to generative AI research, several limitations should be considered when interpreting the findings. First, the cross-sectional design restricts the ability to conclude changes in perceived norms, skills, and behaviours over time. As a result, the observed associations should be interpreted as reflective of relationships at a single point rather than as developmental or causal processes. Future longitudinal studies could provide deeper insight into how generative AI use and advocacy evolve as institutional familiarity increases.

Second, because generative AI was still an emerging technology at the time of data collection, participants' levels of familiarity may have influenced how norms, intention, and skills were formed and expressed. Consequently, the findings should be interpreted within the context of early-stage adoption, and future research may consider examining more established information technologies or conducting follow-up studies as generative AI becomes more embedded in professional practice.

Third, the study was limited to academic librarians in Nigerian public universities, which may constrain the generalisability of the findings to other library types or professional sectors. Therefore, the results should be interpreted as context-specific, and future studies may extend the model to public libraries, private institutions, or other industries to assess its applicability across different organisational and cultural contexts.

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