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UTAUT as a Model for Understanding Intention to Adopt AI and Related Technologies among Librarians

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ABSTRACT

This study explored the intention to adopt various AI and related technologies by academic and public librarians. A survey was disseminated through various library organization lists to collect input on issues surrounding AI attitude and intentions among librarians in North America. We utilized the Unified Theory of Acceptance and Use of Technology (UTAUT) as a framework and performed structural equation modeling (SEM) and related statistical analyses (using SPSS and AMOS). Our findings confirm that the UTAUT can partially predict the likelihood of AI and related technologies adoption intentions among librarians. The model showed that performance expectancy (PE) and attitude toward use (ATU) of AI and related technologies had significant effects on librarians' intention to adopt AI and related technologies, while social influence (SI) and effort expectancy (EE) did not. We conclude that UTAUT is a viable integrated theoretical framework that, when properly designed and executed within a study, and lends itself to robust statistical analyses such as SEM. UTAUT is helpful as a framework for future approaches to designing and promoting adoption and use of emerging technologies by librarians.

Introduction

New technological trends, along with their possible impact on library systems, have been identified by The American Library Association (ALA) Center for the Future of Libraries. These trends could have impacts on services and operations, affecting the accessibility of library resources, enhancements to delivery of services, and enhancements to serving users (Bolt, 2014). Many of the new technological advancements in library settings are in research and developmental stages, and there are instances where these evolving technologies have been implemented and their impact observed. As new technologies evolve, librarians must ensure they are prepared to develop, implement, and evaluate rapidly changing advancements that have potential to provide advanced services to users. Furthermore, librarians should be able to holistically evaluate current trends and future directions of technology development and concomitantly respond to evolving user demands.

The advent of new technologies, along with their increasing availability, could lead to gaps in adoption and use among individual libraries. Moreover, the ability of professionals to prepare themselves to adopt current and future technologies could have additional implications for library training and education. These types of issues were the impetus for this study, which seeks to examine adoption of AI and related technologies in librarianship. As central institutions to communities, both public and academic libraries have often exemplified adoption and use of new technologies that can be leveraged to enhance services to users and broaden the overall understanding of their impact. More needs to be understood about what factors might impact librarians' intentions to adopt these in the future.

Some of the most notable changes in technological advancements happened within the first three technological revolutions. The First Industrial Revolution centered around steam powered engines, the Second Revolution came about through the invention of electricity, the Third Revolution took shape with the invention of computers (Khan & Isreb, 2018). Some believe that we are undergoing a Fourth Industrial Revolution through trending technologies such as AI and Machine Learning, IoT, Big Data, Blockchains, Cloud and Edge Computing, Robots and so on (Marr, 2020).

For this study, six technologies were selected to assess academic and public librarian's perceptions toward adopting AI. Park et al. (2018) identified AI, IoT, Cloud computing, Big Data, Robots, and Mobile as technologies for libraries in the era of 4th Industrial Revolution. The phrase "AI and related technologies" is not an all-encompassing term for

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these six technologies and may be up for debate. However, since there is currently no agreed upon, overarching term for these trending technologies included in the 4th Industrial Revolution, we have used “AI and related technologies” as a phrase to refer to the technologies of interest to our research project, as further defined below:

- Artificial Intelligence (AI) revolves around the idea of creating computers and machines that mimic human behavior and ultimately “think” like humans (“Artificial Intelligence,” n.d.). These machines are meant to perform simple tasks and make decisions based on data they have gathered.
- Internet of Things (IoT) refers to the interconnectivity of devices and objects through the internet. Data is collected and then transmitted across multiple devices, platforms, and machines. (Marr, 2020).
- Big Data refers to the vast amounts of data produced in the age of technology (Marr, 2020). As technology advances, more data becomes more easily accessed. With so much data, there are issues in the methods of storage, analysis, and usage.
- Robots can be described as machines able to interact with environments and perform routine tasks in place of a human (Robots, n.d.; Marr, 2020).
- Cloud Computing involves the storage and sorting of data on to other devices (Marr, 2020). This data can be delivered on demand through a data base, server, software or network.
- Augmented Reality/Virtual Reality can be thought of as a set of generated stimuli (this stimuli could be visual, auditory, sensational, or a blend) projected through electronic equipment. These projections can enable users to experience an overlay of the real world or generate an entirely new world that users can interact with (Reality, n.d.; Marr, 2020).

Keeping AI and related technologies in mind, this study is based on the theoretical framework of the Unified Theory of Acceptance and Use of Technology (UTAUT), with some modifications to fit the study's aims and data, to better understand predictors associated with adopting AI and related technologies in libraries. We believe that the study results will help in developing best practices for strategically preparing librarians in the era of the fourth Industrial Revolution. The research question driving this study is, What are the factors affecting academic and public librarians' perceptions of, and intention to adopt AI technologies?

Background

Libraries and AI and related technologies

AI is still a relatively broad term referencing the ability to use deep machine learning techniques to analyze vast amounts of data in support of decision-making. Adding to the complexity is the hyper-connectivity and super-intelligence we are increasingly experiencing through these technologies. For instance, “Internet of Things,” or IoT, technologies are exponentially expanding the connection across one device to another, between humans, and between devices and humans, while technologies such as AI and robotics seek to create machines that can mimic human intelligence across (or, intelligentize) industrial structures (Park et al., 2018). Services such as autonomous vehicles, drone delivery, and real-time automatic voice translation based on intelligent information technology are being applied to enhance our daily lives.

In library environments, there are instances where AI and related technologies have been implemented. For example, in the area of collection management, applications of AI and big data analytics allow librarians to make more efficient collection management and marketing decisions (Crawford & Syme, 2018). AI is also used in the form of Online Chatbots (Gujral et al., 2019), Online Reference Assistance (ORA) (Vijayakumar & Sheshadri, 2019) and Plexus (Mogali, 2014). Then there is the implementation of AI in the User service. Robots with AI technology have been developed to the point of being a reliable substitute for some human services such as use in RFID scanning, shelf reading and inventory management (Smith, 2020; Kim, 2019). Utilizing robots in non-traditional ways expand library service hours and provide services to more users (Yao et al., 2015), such as, 24/7 access to some library services which were typically performed by librarians. The implementation of IoT in library facilities allows for wirelessly connected devices which can interact to personalize information to an individual, provide library services, or acquire data analytics (Liang, 2018). Beacon alerts, user location notifications, access and reading seat assignments, route guidance, smart indoor air quality monitoring, and lockers and mobile self-loan service are the examples of utilizing IoT. In the area of user education, programming initiatives for technology and making are increasingly in demand and valued by users. Librarians are not only creating Making opportunities for users to explore new technology (Finley, 2019), but also new technology into educational offerings (Lessick & Kraft, 2017).

Research on technology adoption in libraries

Over the past few decades, libraries have become increasingly enmeshed with the technological world. Many technologies that were once considered groundbreaking, are now expected in libraries as common resources. For instance, online portals, web-based collections, and computerization (Chang, 2013; Crawford & Syme, 2018; Gul & Bano, 2019; Wood & Evans, 2018) were all considered revolutionary when first implemented.

Adoption of technologies in library settings have been viewed through technology adoption models that seek to explain influencing factors. Among the various models, Technology Adoption Model (TAM) (Davis, 1989; Malhotra & Galletta, 1999) and the extended TAM, known as the Unified Theory of Acceptance and Usage of Technologies (UTAUT) (Venkatesh et al., 2003), are popularly used models in the library environments. TAM illustrates that External Variables (such as demographic variables), Perceived Usefulness, and Perceived Ease of Use are the determinant of Attitude toward Use, Perceived Usefulness and Attitude toward Use are the determinant of Behavioral Intention to Use and subsequent Actual Use. UTAUT distinguishes between determining factors (Performance Expectancy, Effort Expectance, Social Influence and Facilitating Conditions) and mediating factors (Gender, Age, Experience, and Voluntariness of Use), and illustrates that these determining and mediating factors influence on Behavioral Intention and subsequent Use Behavior. These four factors help shape an individual's positive or negative judgement when encountering a new technology (Akwang, 2021).

In LIS areas, there are studies which utilized TAM and UTAUT for exploring factors affecting the adoption of new technologies, such as, Internet, mobile services, and digital library services, on librarians/information professionals. Spacey et al. (2004) explored UK public library staff's attitudes toward the Internet using the TAM and revealed that usefulness, intention, and actual usage are related to the attitudes. Sheikhshoaei and Oloumi (2011) examined the determinant factors of Iranian academic librarians' acceptance of Information Technology (IT), and reported that all of TAM variables (perceived usefulness, perceived ease of use, attitude toward use, and the intention to use) affect the acceptance of IT. Aharony (2013) explored Israeli academic, public and special librarians' perceptions of mobile services, and demonstrated that TAM's two components (perceived ease of use and usefulness) and two additional components (personal innovativeness and smart phone usage) are related to librarians' intention to use of mobile services. Gholami et al. (2018) utilized the model integrating TAM and TOE (Technology Organization and Environment) model for examining determinant factors of adopting mobile technology-based services by Iranian academic librarians, and identified perceived ease of use, perceived usefulness, compatibility, relative advantage, and organizational competency as determinant factors. Using the TAM, Aharony (2015) reported that perceived usefulness, perceived ease of use, personal innovativeness and other personal characteristics are factors affecting the intention to use e-books among librarians and information specialists in Israel.

Khan et al. (2017), by utilizing UTAUT, revealed that usefulness, ease of use and information and communication technology skills as the factors affecting adoption of digital reference services among the university librarians in Pakistan. Zainab et al. (2018) examined the acceptance of RFID based LMS (Library Management System) by university librarians in Malaysia, using the UTAUT with two additional determinants, attitude and self-efficacy, and revealed that performance expectancy, effort expectancy, attitude toward technology, social influence and self-efficacy are the determinants of librarians' acceptance of RFID based LMS.

Izuagbe et al. (2019), although they adopted either TAM or UTAUT, examined if Perceived ease of use and e-skill are determinants of technology acceptance intention among librarians, and reported that the e-skill is the strong determinant, and the Perceived ease of use is a significant moderator of librarians' acceptance intention when e-Skills are insufficient.

The above studies consistently revealed that TAM and UTAUT factors' influence on technology adoption among librarians (see Table 1). However, it was found that there seems to be a lack of studies in North America that have used these two models. The present study attempts to utilize the UTAUT for understanding factors impacting AI related technology adoption among academic and public librarians in North America.

Table 1
Related studies utilizing TAM or UTAUT for librarians and information professionals.

Study	Context	Utilized model	Determinant factors	Affected factor
Aharony (2013)	Librarians' perceptions of mobile services (m-service) (Israel)	TAM	Perceived ease of use Perceived usefulness Personal innovativeness[a] Smartphone usage[a]	Behavioral intention to use m-service
Aharony (2015)	Information professionals' attitudes toward e-book adoption (Israel)	TAM	Perceived usefulness Perceived ease of use Personal innovativeness[a]	Behavioral intention to use e-books
Gholami et al. (2018)	Academic librarians' mobile technology adoption at libraries (Iran)	TAM/TOE	Perceived usefulness Perceived ease of use Compatibility[a] Relative advantage[a] Organizational competency[a]	Attitude toward mobile technology adoption
Khan et al. (2017)	University librarians' digital reference service adoption (Pakistan)	UTAUT	Perceived ease of use Perceived usefulness Information and communication skills[a]	Intention to adopt digital reference services
Sheikhshoaei and Oloumi (2011)	University librarians' Information Technology acceptance (Iran)	TAM	Perceived usefulness Perceived ease of use Attitude toward use Behavioral intention to use	Actual system use
Spacey et al. (2004)	Public librarians' attitudes toward use of the Internet (UK)	TAM	Perceived usefulness Behavioral intention to use Actual use of computer and the Internet	Attitudes toward use of the Internet
Zainab et al. (2018)	University librarians' acceptance of RFID-LMS (Library Management System) (Malaysia)	UTAUT	Performance expectancy Effort expectancy Attitude toward using technology[a] Social influence Self-efficacy[a]	Acceptance of RFID based LMS

[a] Factors not included in the original TAM and UTAUT.

Conceptual framework and hypotheses

Conceptual framework

Our project seeks to expand on a growing body of research into how librarians (and similar service-oriented information professionals) integrate new technologies in both professional practice and in enhancing service to users. We adopted the Unified Theory of Acceptance and Use of Technology (UTAUT) as the theoretical framework. UTAUT is an integrated, causal model developed for describing and predicting technology acceptance and use in various fields and has been empirically tested for validity and reliability in several previous studies (Dowdy, 2020; Khan et al., 2017; Šumak & Šorgo, 2016; Venkatesh et al., 2003).

The UTAUT, as originally conceived, integrates eight technology acceptance models that help identify factors determining individuals' technology acceptance, and is organized around the specific constructs of *Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Conditions* (Venkatesh et al., 2003). For this study, we initially used these four determining factors and also included *Attitude toward using technology*. Attitude toward using a given technology was also originally included in the original UTAUT survey by Venkatesh, but was later omitted since they did not show direct effect. In our study, our research model shown in Fig. 1 includes *attitude toward using* technologies as one of four main factors likely to impact intention to adopt. Our rationale was that it has been shown that professionals in other fields (law and medicine, for instance) have divided attitudes on AI adoption for their professional work (Wood & Evans, 2018), and we postulate that this could be a factor in understanding our research question. Our model was further modified as shown in our data analysis, below; to wit, *facilitating conditions,* as measured by the survey instrument, did not show appropriate reliability so was taken out of the model. Other factors contributing to certain latent variables were trimmed based on analysis of the model's fit. Below, we discuss the key constructs and resulting hypotheses based on the model and research questions.

In addition to the above determining factors, UTAUT identifies other factors that might moderate the impact of the determining ones. For instance, originally UTAUT identified Gender, Age, Experience, and Voluntariness of use as mediating factors; however, in this study we revised these moderators as follows. First, the impact of librarians' experiences with AI and related technologies for their work on the intention to adopt AI and related technologies were analyzed. We also included control variables for certain demographic variables (age and gender). And, similar to Khan et al. (2017), we included library type as a moderating factor in our conceptual model (e.g., organizational characteristics). Thus, the following mediating factors have been adopted in our conceptual model:

- *Experience with AI and related Technology*: Current use of systems/service utilizing AI and related Tech
- Personal Characteristics: Age and Gender.
- *Organizational Characteristics*: Library type: Academic or Public.

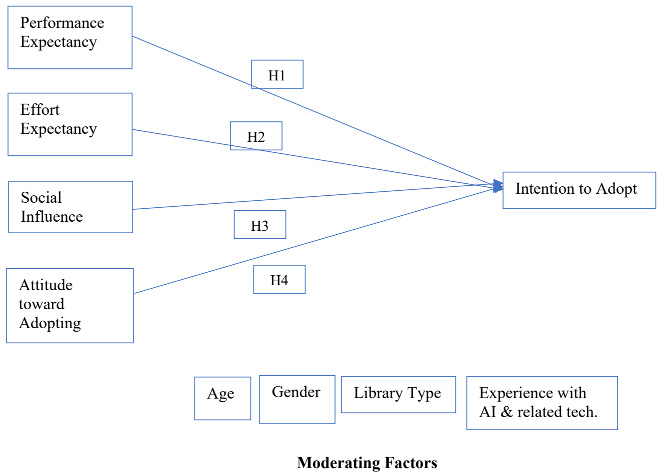

Fig. 1. Adopted UTAUT conceptual framework.

Research hypotheses

Performance Expectancy (PE)

Performance expectancy (PE) is the perceived usefulness of adopting a system and the belief that the use of the adopted system will aid them in their job performance (Venkatesh et al., 2003). In the context of this study, PE will be explored in relation to AI and related technologies for library systems and services.

H1. . PE will have an effect on Intention to Adopt AI and related technologies.

H1a. . The influence of PE will be moderated by gender, library type, and experience.

Effort Expectancy: (EE)

Effort Expectancy (EE) is defined by Venkatesh et al. (2003) as the level of ease in adopting the use of a system. In the context of this study, the ease of adopting and use of AI and related technologies for library systems and services will be explored.

H2. . EE will have a significant effect on Intention.

H2a. . The influence of EE will be moderated by gender, library type, and experience.

Social Influence (SI)

Social Influence (SI) is described by Venkatesh et al. (2003) as how an individual perceives the degree that “important others” think that they should adopt the use of a new system. In the context of this study, outside influences on a person's perception regarding adopting AI and related technologies for library systems and services will be explored.

H3. . SI will have a significant influence on Intention.

H3a. . The influence of SI will be moderated by gender, library type, and experience.

Attitude toward adopting AI and related technologies (ATU)

Attitude toward the adoption of AI refers to the preferences, including positive feelings, negative ones, or apprehension regarding intentions to adopt these AI and Related Technologies in library systems and services.

H4. . ATU will have a significant influence on Intention to adopt AI and related technologies.

H4a. . The influence of ATU will be moderated by gender, library type, and experience.

Research design

The survey questionnaire was built around the adopted and revised UTAUT, modifying some factors and wording to better reflect the uniqueness of the technologies of interest as relevant to libraries (see Appendix A). From these we utilized an online questionnaire (using Qualtrics) that surveyed both academic and public librarians across North America and Canada. We sought to recruit those who are active in the community as assumed by participation on relevant listservs of ALA committees and key national organization lists. IRB exemption approval was received, and selected various professional listservs were used to send invitations out requesting participants for the online surveys. The listservs selected were from library associations in order to increase recruitment of practicing academic and public librarians. The following is a list of the listservs solicited: The American Library Association's Machine and Deep Learning Research Interest Group, Library and Information Technology Association List, Association of College and Research Libraries (ACRL) Science & Technology Section Discussion List, Advocacy for Libraries, Library and Information Technology Association (LITA) Instructional Technologies Interest Group Email List, Center for Research Libraries (CRL) Systematic Reviews & Related Methods Interest Group, Community and Junior College Libraries Section (CJCLS) Section, Association for Library Collections & Technical Services (ALCTS) Catalog Form and Function, ACRL New Members Forum, ACRL First Year Experience Discussion Group, and the Public Library Association (PLA)'s main discussion board.

Data collection took place from November 16th, 2020 until January 6th, 2021. A total of 340 responses were collected, however 20 responses were eliminated due to participants not being a public or academic librarian, and/or their not being able to move forward within the questionnaire. Other responses were excluded due to the survey not being fully completed, making their responses incompatible within our analysis. This resulted in a final dataset of 236 participant responses. Upon survey completion, participants who opted to submit their email address for compensation were awarded a $10 Amazon gift card.

The statistical analyses supporting the SEM approach were conducted with SPSS (v. 27) and its supporting modeling software, AMOS (v. 27).

Results

Table 2 is a breakdown of basic characteristics of the respondents. Of the 236 participants, 115 were academic librarians (48.7%) and 121 were public librarians (51.3%), the vast majority hold an MLIS degree (n = 205), and a large percentage (76.7%) reported their gender as female. Other descriptive data related to the respondents relates to race and ethnicity, experience working as a librarian, and other information to help contextualize the study sample. Also, Appendix B presents descriptive feature of participants' job responsibilities.

Our survey instrument included Likert scale (1-Strongly Agree to 5-Strongly Disagree) questions to measure the valid UTAUT measures adopted from Venkatesh et al. (2003). Internal reliability of the scales was assessed via Cronbach's α set at 0.70 as proposed by others (Khan et al., 2017; Šumak and Šorgo (2016)). Table 3, below, reveals that each of the constructs were above the 0.70 threshold except for those measuring Facilitating Conditions. Relatively low Cronbach test result for this was also true in Šumak and Šorgo (2016). Although some, as noted in Sarkam (2019), cite the possibility of using a lower threshold of 0.60, this is not common, and we chose not to include this as a valid element of the model since the measures used did not have internal reliability. Our decision was further evident later in the exploratory factor analysis (below).

Common method effect

Following standard practice to further explore potential

Table 2
Respondent characteristics.

		Frequency	%
Gender	Male	43	18.2%
	Female	181	76.7%
	Other	5	2.1%
	No response	7	3%
	Total	236	100%
Age group	24 or younger	3	1.3%
	25–34	53	22.5%
	35–44	67	28.4%
	45–54	51	21.6%
	55–64	43	18.2%
	64 or older	13	5.5%
	No response	6	2.5%
	Total	236	100%
Ethnicity	Asian	7	3%
	Black or African American	6	2.5%
	Caucasian	193	81.8%
	Hispanic/Latino	7	2.5%
	Native American	1	0.4%
	Mixed Race	8	3.4%
	Prefer not to respond	13	5.1%
	Other	3	1.3%
	Total	236	100%
Experience as a librarian	Less than 5 years	39	16.5%
	5 to less than 10 years	64	27.1%
	10 to less than 15 years	49	20.8%
	15 to less than 20 years	32	13.6%
	20 to less than 25 years	19	8.1%
	25 to less than 30 years	19	8.1%
	More than 30 years	14	5.9%
	Total	236	100%
Position	Librarian	213	88%
	Other professional staff	18	7%
	Para-professional	8	3%
	Other	4	2%
Possess MLIS	Yes	205	86.9%
	No	25	10.6%
	Currently pursuing	6	2.5%
	Total	236	100%
Library type	Public	121	51.3%
	Academic	115	48.7%
	Total	236	100%
Current AI use in library	Yes	49	20.8%
	No	183	77.5%
	No Reply	4	1.7%
	Total	236	100%
How do you keep professional trends[a]	Journal/Magazine articles	215	20.3%
	Social media	149	14.1%
	Listservs	221	20.8%
	Attend professional conferences	219	20.7%
	Webinar	219	21.6%
	Other	27	2.5%

[a] Multiple response question.

Table 3
Measure reliability.

Construct	Items	Cronbach α
Performance Expectancy (PE)	PE_1, PE_2, PE_3	0.894
Effort Expectancy (EE)	EE_I, EE_2, EE_3	0.827
Social Influence (SI)	SI_1, SI_2, SI_3[a]	0.766
Facilitating Conditions (FC)[a]	FC_1, FC_2, FC_3	0.615 (not included; below threshold)
Attitude Toward Using (ATU)	ATU_1, ATU_2, ATU_3[a]	0.802
Intention to Adopt AI Tech (IntUse)	IntUse_1, IntUse_2	0.923

[a] Removed from final measurement model.

measurement errors (Khan et al., 2017; Podsakoff et al., 2003), we performed a measure of common method variance (CMV). This is essentially a factor analysis limited to a result of a single factor to determine amount of variance or bias. It is generally recommended that this should be <50%. Our CMV result was 35% indicating no measurement error or bias.

Measurement model

After evaluating the measures, a measurement model was created using AMOS (v.27) that links UTAUT constructs represented as latent variables and their corresponding observable data elements or indicators that were measured by the survey instrument. Covariances between all latent variables are drawn as part of the model development. The initial measurement model was in part determined using exploratory factor analysis in SPSS (v.27) using principal axis factoring forcing a 5-factor solution and a Promax rotation. Generally, a KMO (Kaiser-Meyer-Olkin) statistical test of 0.80 or greater is considered very good in determining suitability of data for factor analysis. The KMO test for our data was 0.852 and significant at a level of $p < .001$.

The factor analysis, as similarly reported in the Cronbach alpha tests earlier, showed that Facilitating Conditions was not a good fit in any grouping and was therefore removed. This was further supported as that factor was below the threshold in the measure of communalities that determines the extent to which an item correlates with all the other items.

Resulting data on the convergent reliability (where CR > 0.7; AVE > 0.5) and discriminant validity (DV; wherein the square root (bold number) of AVE > inter-construct correlations) (Hair et al., 2010) tests are shown in Table 4 and matrix in Table 5, respectively. The data in Table 3 shows the final model constructs and factor model results after having removed two variables that did not show appropriate fit into the model. These were ATU_3 ("Adopting AI and related technologies in libraries is somewhat intimidating to me"); and, also SI_3 ("In general, my library has positive views on adopting AI and related technologies to enhance library services"). The remaining factor loadings are all at, or exceed, acceptable levels, which is also revealed in the CR (composite reliability).

Following the CR and DV testing above, a test of the fitness of the resulting model was conducted using AMOS. A summary of the results of the main fit measures is shown in Table 6. That table displays common measures of fitness used when testing a structural model, the recommended criteria for each, and how our measurement model scored. All criteria are within the recommended ranges.

In addition to a structural measurement of the model as described and shown below, we conducted additional analyses that controlled for Experience, Age, and Gender. None of these had significant effects and therefore do not act as confounds to the model.

Table 4
Convergent validity assessment summary.

Model construct	Item	Factor Loading	CR	AVE	MaxR (H)
Performance Expectancy (PE)	PE_1	0.8480	0.858	0.751	0.860
	PE_2	.9160			
	PE_3	.693			
Effort Expectancy (EE)	EE_1	0.6850	0.830	0.622	0.844
	EE_2	.8840			
	EE_3	.790			
Social Influence (SI)	SI_1	0.9770	0.810	0.606	0.934
	SI_2	.785			
Attitude toward use (ATU)	ATU_1	−0.877	0.854	0.746	0.904
	ATU_2	−0.740			
Intention to adopt (IntAdopt)	IntAdopt_1	0.7250	0.925	0.861	0.945
	IntAdopt_2	.927			

Table 5
Discriminant validity findings.

	ATU	EE	SI	IntAdopt	PE
ATU	0.864				
EE	−0.202	0.788			
SI	−0.505	0.234	0.898		
IntAdopt	−0.786	0.169	0.571	0.927	
PE	−0.756	0.133	0.618	0.800	0.866

Table 6
Model fit summary for the final measurement model.

Fit Index	Recommended criteria	Measurement model
Chi square (x^2)	Non-sig	76.85
Degrees of Freedom		44
x^2/df	<3.00	0.002
Goodness of Fit Index (GFI)	>0.90	0.948
Adj. Goodness-of-fit index (AGFI)	>0.80	0.908
Comparative fit index (CFI)	>0.90	0.983
Root mean square residual (RMR)	<0.10	0.032
Root mean square error of approximation (RMSEA)	<0.08	0.056
Parsimony normed fit index (PFNI)	>0.60	0.641

Fig. 2 shows the resulting structural model as graphically created and measured in AMOS. The overall R^2 was strong at 0.722, for Intention (the outcome variable). All coefficients contributing to the latent variables were shown to be significant, further reflecting a valid model. As shown in Table 7, as well as Figs. 2 and 3, performance expectancy (PE) (β = 0.463; p < .001) and attitude toward use (ATU) (β = −0.343; p < .001) of technology have significant effects on librarians' intention to adopt AI and related technologies. Thus, the H1 and H4 hypotheses were supported, while H2 and H3 were not supported since effort expectancy and social influence did not show significant effect.

We tested the effects of moderating factors of gender (male and female), library type (academic and public), and current use of AI and related technologies (yes or no) by utilizing multigroup analysis (Table 8). For each of these multigroup analyses, PE and ATU again showed effects on intention to adopt/use AI and related technologies, with no differences between group 1 and 2 in any. We ran a Chi-square difference test for each group with the unconstrained and constrained (only individual path) models and found no significant differences, as well.

Table 7
Hypothesis results.

Hypothesis	Coefficient	P value	Supported
H1: PE - > Intention to adopt	0.463	<0.001***	Yes
H2: EE - > Intention to adopt	0.007	0.895	No
H3: SI - > Intention to adopt	0.110	0.092	No
H4: ATU - > Intention to adopt	−0.340	<0.001***	Yes

*** p < .001.

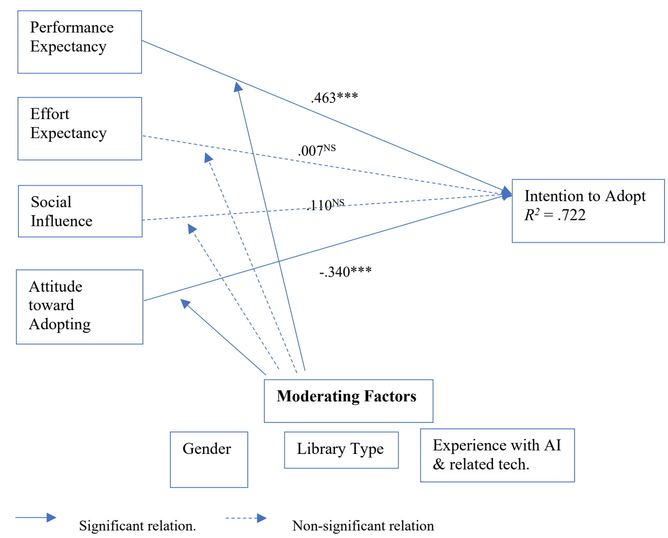

Fig. 3. Summarized structural model analysis
→Significant relation. →Non-significant relation.

Discussion

This study used the theoretical framework of UTAUT tailored to explore some general perceptions on intention to adopt AI and various related technologies by public and academic librarians. The UTAUT framework helped us design and test a structural equation model (SEM), based on survey data we collected from a sample of librarians that was valid and helped elucidate some important findings. The findings confirm that the UTAUT can partially predict the likelihood of AI and related technologies adoption intentions among librarians, particularly highlighting the importance of PE (performance expectancy) and ATU

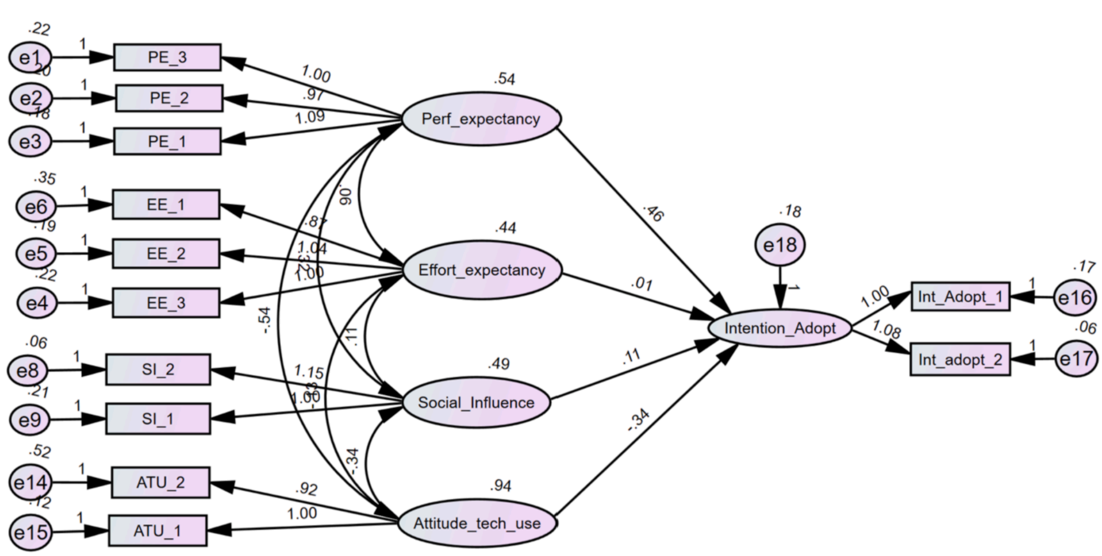

Fig. 2. Structural model (AMOS Output).

Table 8
Results of moderation analysis.

	PE - > Int	EE - > Int	SI - > Int	ATU - > Int
Male	1.025***	−0.019	−0.064	−0.238*†
Female	0.351***	0.007	0.093	−0.374***
Academic	0.439***	−0.023	0.170	−0.349***
Public	0.445**	0.030	0.073	−0.336***
Current AI use	0.336*	−0.126	0.157	−0.342***
No current AI use	0.547***	0.089	0.072	−0.301***

* $p < .05$ (†ATU- > Int for Male group 0.055).
** $p < .01$
*** $p < .001$.

(attitude toward use).

First, we learned that PE (performance expectancy) and ATU (attitude toward use) have significant impact on one's intention to adopt these technologies. It has been revealed that the PE (UTAUT) and Perceived usefulness (TAM) are the strong determinants on new technology acceptance, as shown in Fridin and Belokopytov (2014) which examined the acceptance of assistive humanoid robots by schoolteachers via UTAUT. Spacey et al. (2004) similarly explored UK public librarians' attitudes toward the Internet through the perspective of TAM. In the context of our study, this seems to also make intuitive sense. Librarians in both academic and public libraries ostensibly need to have high levels of the perceived usefulness of a technology before considering it as something to adopt in their organization and to better serve their user communities. Their attitudes toward adopting these would similarly impact such actions, as well. Attitude is a component of TAM but not of UTAUT model. Attitude was originally included in the UTAUT survey but later omitted since it does not show direct effect (Venkatesh et al., 2003). However, the current study demonstrated that attitude can have significant impact on librarians' intention to adopt AI and related technologies, which is the consistent result with Zainab et al.'s (2018) study. The fact that there was no difference between the two groups (academic versus public) shown in the multigroup analysis, adds further strength to the result.

In addition, EE (effort expectancy) and SI (social influence) did not show a significant impact on intention to adopt these technologies. As shown in the Background section and Table 1, EE (UTAUT) and Perceived ease of use (TAM) have been reported as determinants of technology acceptance in most studies. However, there are also studies reported that EE and SI have less significant in explaining the intention of adoption new technologies. Chang (2013), which examined library users' intention of using library mobile applications, concluded that peer influence is less important when users have a higher task-technology fit based on the findings that SI was negatively influence on the intention of use. Khan et al. (2017) examined the adoption of digital reference services (DRS) among university librarians in Pakistan via UTAUT, and reported that ease of use is less supportive in the adoption of DRS and usefulness is the strongest factor. Aharony (2015) and Spacey et al. (2004) also reported that ease of use is less significant than usefulness. Khan et al. (2017) suggested that, based on their findings, "librarians will not adopt DRS if it is only easy to utilize but not useful" (p.1238). We share this belief based on our findings for librarians' adoption of AI and related technologies. However, since these previous studies showed only less significance of EE and SI, not a complete absence of significance, it is difficult to speculate with any accuracy as to why neither EE nor SI were supported as significant in the model. The measures used for each were reliable, (except one in SI) and they have contributed in other UTAUT-based contexts. One possibility could be found in the fact that there is still some vagueness on what "AI and related technologies" includes, and also only some limited implementation of the technologies we bring into the survey by libraries at this point. Also, we did not account for differences in the roles of each librarian, and it is possible that the effort actually expended on such technologies could be under- or mis-estimated by those not directly involved in their implementation. Thus, self-reported feelings of what effort might be required in adopting such technologies could be somewhat low. Looking at the mean for each, they are below 3 and suggests no strong feelings one way or the other. The lack of current adoption and, thus, discussion from other librarians and peers might have had similar effects on responses to SI. What level of social influence is being applied to librarians if not many of their colleagues are using AI and related technologies. This has shown much stronger effect in studies of more common technology adoption.

This study has several limitations. First, we sought to recruit nationwide academic and public librarians who are active in the community, as assumed by participation on relevant listservs of various ALA committees and key national organization lists. However, the survey data has selection and nonresponse biases favoring those who subscribe the selected listservs and who respond to surveys, and the biases would limit the generalizability of findings. Second, the six AI and related technologies that we examined are popularly used terms in our lives through various media. So, we asked librarians' perceptions on these six technologies based on their general knowledge. There is always room for misunderstanding of terms in a survey, and we acknowledge that there were possibilities that participants might have inconsistent understandings on six technologies. Despite the limitations, this study provides us with some insights in moving forward with promoting new, advance technological tools. If new tools are to be adopted by librarians, at least academic or public librarians, attention should be given to the potential usefulness of these to supporting the core functions of libraries. Similarly, promotion of new technologies will likely need to take into account the effort librarians may feel is needed to appropriately integrate these into their organizations. Eventually, their experiences might influence other librarians' intention to adopt AI and related technologies.

Conclusions

Our investigation found that UTAUT is a viable theoretical framework for exploring librarians' attitudes toward adoption and use of AI and related technologies, such as the ones of interest in this study. When properly designed and executed, this framework lends itself to robust statistical analyses, such as SEM, and can be applied in future approaches to designing and promoting technology adoption in library settings.

There is an apparent lack of studies utilizing UTAUT as a framework by LIS researchers. Those studying technology adoption and use may see our work as evidence for future investigations. We suggest it is necessary to conduct other studies across similar contexts to explore why EE and SI do not seem to impact these behaviors and intentions, and to better build in one's function viz *a* viz technology as a potential factor influencing these constructs. Moreover, other analyses could build a model to include moderating variables between the main constructs and outcome variable(s) or other causal effects. Researchers may consider designing and testing different instruments that focus on specific technologies to gain a more precise indication of intention to adopt or plans for future use.

Ultimately, research of this sort will help LIS educators and practitioners plan for the likely integration of AI and related technologies in their libraries. The results of this research should be used to develop education and training strategies to ensure librarians are prepared for the next phase of technological adoption.

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CRediT authorship contribution statement

James E. Andrews: Conceptualization, Methodology, Formal analysis, Writing – Original Draft, Writing – Review & Editing, Visualization, Supervision, Project administration, Funding acquisition. **Heather Ward:** Formal analysis, Writing – Original Draft, Writing – Review & Editing. **JungWon Yoon:** Conceptualization, Methodology, Writing – Original Draft, Writing – Review & Editing, Project administration, Funding acquisition.

Appendix A. UTAUT factors and survey questionnaire

Factors	Questions
Personal characteristics	• Demographic questions (Age, Gender, and Ethnicity) • Years working as librarian • Current position and primary job responsibility • Holding MLS/MLIS degree • Venues of keeping professional trends
Organizational characteristics	• Type of library (academic/public) ○ For academic library, type of academic library ○ For public library, Key community served
Experience with AI Technology	• Do you currently use systems/services utilizing AI and related technologies?
Performance Expectancy (PE)[a]	1. I would find AI and related technologies useful for my library. 2. Adopting AI and related technologies in library will enable us to provide more advanced services. 3. Adopting AI and related technologies in the library will enable us to provide services more effectively.
Effort Expectancy (EE)_[a]	1. I am confident I could become skillful at systems/services adopting AI and related technologies. 2. I would find systems/services adopting AI and related technologies easy to use. 3. Learning to operate systems that utilize AI and related technologies is easy for me.
Social Influence (SI)[a]	1. People who influence me think that libraries should adopt AI and related technologies. 2. People whose opinions I respect think that libraries should adopt AI and related technologies. 3. In general, my library has positive views on adopting AI and related technologies to enhance library services.
Facilitating Conditions (FC)[a]	1. I have (or would have) the resources to use systems/services adopting AI and related technologies. 2. I have the knowledge necessary to use systems/services adopting AI and related technologies. 3. A specific person (or group) is (would be) available for assistance with systems adopting AI and related systems.
Attitude toward using AI and related technology (ATU)[a]	1. I don't like the idea of adopting AI and related technologies in libraries. 2. I feel apprehensive about adopting AI and related technologies in libraries. 3. Adopting AI and related technologies in libraries is somewhat intimidating me.
Intention to adopting AI and related technologies (IntAdopt)[a]	1. I support adopting services/systems adopting AI and related technologies in my library. 2. I support adopting services/systems adopting AI and related technologies in libraries, overall.

[a] Adopted and adopted from the UTAUT survey (Venkatesh et al., 2003).

Appendix B. Participants' job responsibilities*

Academic librarian			Public librarian[a]		
Job responsibility[a]	Freq.	%	Job responsibility	Freq.	%
Reference, public services	89	17.98	Reference, public services	90	15.60
Instruction, learning support	89	17.98	Instruction, learning support	42	7.28
Metadata and cataloging	23	4.65	Metadata and cataloging	32	5.55
Special collection, subject development	6	1.21	Special collection	13	2.25
Administration, budgeting, planning	24	4.85	Administration, budgeting, planning	67	11.61
Acquisitions, collection development	40	8.08	Acquisitions, collection development	66	11.44
Outreach, marketing	32	6.46	Outreach, marketing	57	9.88
Open access, APC management	10	2.02	Interlibrary loan, circulation	29	5.03
Interlibrary loan, circulation	9	1.82	Technology	50	8.67
Technology	43	8.69	Children/youth services	51	8.84
Subject librarian/liaison - health science	16	3.23	Adult services	67	11.61
Subject librarian/liaison - business	11	2.22	Others	13	2.25
Subject librarian/liaison - arts and humanities	22	4.44			
Subject librarian/liaison - social sciences	25	5.05			
Subject librarian/liaison - science, technology, engineering	37	7.47			
Others	19	3.84			
Total	495	100.00	Total	577	100.00

[a] Multiple response question.

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