https://dx.doi.org/10.4314/dujopas.v9i1b.1
ISSN (Print): 2476-8316
ISSN (Online): 2635-3490
Dutse Journal of Pure and Applied Sciences (DUJOPAS), *Vol. 9 No. 1b March 2023*

Investigating Librarians' Intention to Use Artificial Intelligence for Effective Library Service Delivery: A Partial Least Square-Structural Equation Modeling-Based Approach

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Abstract
*Due to the information exploration coupled with the increased number of library users across the globe, servicing the users efficiently and in a simple manner became difficult, leading librarians to think of a better alternative. Artificial intelligence is one of the best options to mitigate issues of inefficient service delivery but has not been used enough in most Nigerian academic libraries and specifically North-eastern Nigerian academic libraries. This research, therefore, aims at examining the factors that can influence the librarians' intention to use artificial intelligence in their libraries for better and more efficient service delivery to library patrons using the theoretical lenses of the Theory of Plan Behaviour (TPB). A quantitative method using a cross-sectional approach was adopted and a questionnaire was used as an instrument for data collection. Three federal university libraries from North-eastern Nigeria were covered and 242 professionals and para-professionals librarians composed the population of the research. G*Power application was used to estimate the minimum sample size of the research amounting to 119 samples thus, a proportionate stratified random sampling technique was used in obtaining the sampling. Statistical Package for Social Science (SPSS) version 20 and Partial Least Square – Structural Equation Modelling (PLS-SEM) were used to analyze the data. The findings revealed that TPB's theoretical variables were positively significant factors that influenced the librarians' intention to use Artificial Intelligence in their respective libraries. Equally, the finding further revealed that the librarians indicated a high intention to use artificial intelligence in their libraries. The use of more advanced theory, the inclusion of more samples and considering a specific artificial intelligence tool were recommended for future research.*

Keywords: Academic libraries; Artificial Intelligence; North-east Nigeria; library service delivery, librarians' intention.

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INTRODUCTION

The technological breakthrough currently going on across the globe changes all spheres of life and libraries are not in exception. Several technologies have been used and influencing library services to the extent that library patrons are more enticed than ever before (Lund et al., 2020). Academic libraries are units domiciled in higher educational institutions primarily designed to provide knowledge-based information and other academic-based support to the institutions' community for the overall attainment of their academic pursuits (Okpokwasili, 2019). Academic libraries are saddled with the responsibility of acquiring, processing, storing and disseminating knowledge-based resources to sustain the academic gold of their parent educational institutions (Akpohonor, 2005). However, sometimes they find it difficult to do so efficiently due to the information explosion and too many requests from the teeming patrons (Schreur, 2020). This, therefore, necessitates the need for sophisticated technological intervention such as the utilization of artificial intelligence to curb the ineffectiveness of library services.

Artificial Intelligence (AI) is another innovation that intelligently uses machines to do what humans can do and perform more faster than humans at processing vast volumes of data and making predictions (Wheatley & Hervieux, 2019). While the enormous amount of data generated every day would require a long time to be processed, AI technologies that use machine learning can swiftly transform that data into useful knowledge (Ajani et al., 2022). The cost of processing the enormous amounts of data that AI programming demands is now the main drawback of employing AI. Nevertheless, researchers testified that the benefits of AI to its users significantly outweigh its cost (Ali et al., 2020). For instance, Hayani et al. (2021) acknowledged that when properly utilized, AI can enhance its users' productivity, economy, and decision-making process, as well as solving complex problems and manage repetitive task accurately than ever before.

AI is one of the most recent digital transformations that academic libraries can unlock its potentials to provide patrons with varying library service alternatives more conveniently (Arlitsch & Newell, 2017). Currently, the field of artificial intelligence (AI) has the ability to update, improve, and supplement many digital applications, providing these technologies with some autonomy without the need for human intervention (Ali et al., 2020). A number of fields which include but are not limited to medicine and surgery, the automobile and aviation industries, commerce and industry, education, and other related disciplines are impacted by artificial intelligence. Therefore, considering its attempt to widespread, academic libraries should also make effort toward harnessing its potential.

Despite the benefits that AI offers to users across different sectors, contexts and countries, researchers revealed that integrating AI in academic libraries of developed countries is very low and still not clear (Wheatley & Hervieux, 2019). likewise in developing countries' academic libraries (Arlitsch & Newell, 2017), the situation is even worse in Nigerian academic libraries which indeed causes library services somehow inefficient, cumbersome and difficult to properly handle(Ajani et al., 2022). Library service efficiency is declining due to unprecedented in-and-out of information in the libraries (Hayani et al., 2021). Attending to all users' requests tend to be impossible as a result of too much of it (Kayode et al., 2020; Makinta et al., 2019).

Issues leading to low adoption of such technology include lack of interest, as a result of poor attitude toward it, lack of awareness about the technology, lack of self-efficacy on the part of the users and many more (Nakhoda & Tajik, 2017). Consistent and appropriate use of AI has been realized as the most effective next solution to handle such difficulties in libraries (Hayani et al., 2021). The discussions about how AI would affect libraries, however, have only begun in recent years (Hervieux & Wheatley, 2021), especially in developing countries. Over the years some academic libraries in developed countries initiated the integration of AI in their services to assist them to deliver a free and efficient service to library patrons (Hervieux & Wheatley, 2021). In an attempt to address the situation, this research aims to investigate the librarians' behavioural intention toward using AI for effective library services delivery in some Northeast academic libraries.

Based on the extant literature, there is extremely scarcity of research that investigates the use of Artificial intelligence in Northeast Nigerian academic libraries. This research, therefore, covers librarians in three selected Federal Universities in Northeast Nigeria which comprises Abubakar Tafawa Balewa University, Bauchi State; Federal University, Kashere, Gombe State and Army University Biu, Borno State. Theoretical variables of the Theory of planned behaviour are utilized to determine the librarian's intention toward the use of artificial intelligence. Based on that, this research aims to achieve the following objectives:

1. To examine the extent of librarians' intention to use artificial intelligence in the academic libraries
2. To examine the determining variables influencing the adoption of artificial intelligence in the academic libraries
3. To develop and test a model for the intention to use artificial intelligence in the academic libraries

Research Hypotheses and Model Developments

Theory of Planned Behaviour (TPB) is utilized to ground and support this research by citing its variables as determining factors that can influence the librarians' intention to adopt AI tools in managing their respective libraries services delivery. Person's attitude, control behaviour and subjective norm of the society he/she belongs to, influence his/her intention and eventually lead to the final behaviour (Kan et al., 2020; Wolitski & Corby, 2015). Several researchers such as (Conner & Armitage, 1998; Gaston & Gerjo, 1996; Hagger et al., 2002; Kan et al., 2020; Pourmand et al., 2020; Siqueira et al., 2022; Wolitski & Corby, 2015) analysed and utilized TPB variables in their quest to determine factors influencing one's behaviour toward a given action and found that the theory is robust and suitable in predictions.

For instance, an attitude which is defined as one's expression of a positive or negative assessment of doing a given behaviour (Kan et al., 2020) was used by Siqueira et al. (2022) and found that it is a good predictor of a person's intention on a given action. Attitude measures the personal feelings of an individual and evaluates his/her behaviour (Wolitski & Corby, 2015). Meaning it measures how positively or negatively a person views a specific behaviour. Conner and Armitage (1998) and Siqueira et al. (2022) justified that users' behaviour toward certain actions is mostly influenced by their initiated attitude. Likewise Arlitsch and Newell (2017) stresses that the attitude of individuals is greatly influencing them to commit some actions and confirmed that attitude influences the adoption of AI adoption. Attitude equally measures whether the users see a given behaviour or action as good or bad. Kumar et al. (2019) affirmed that several studies testified to the positive effect of attitude on intention to adopt technologies of various kind.

On the other hand, perceived control behaviour which is viewed as how people perceive the ease or difficulty of carrying out the intended behaviour was used to predict the adoption intention of users and was found to be a significant factor (Conner & Armitage, 1998).

Perceived control behaviour measures a person's personal belief that he /she has control over a given action or behaviour. Wolitski and Corby (2015) and Siqueira et al. (2022) found that perceived control behaviour positively influences users' intention toward certain actions. Moreover, Pourmand et al. (2020) found that perceived control behaviour significantly influences the behaviour of users toward the adoption of innovation such as AI. Perceived control behaviour equally focuses on whether users can successfully carry out a given behaviour or not. Kumar et al. (2019) confirmed that perceived control behaviour has been a good predictor of technology adoption intention in various contexts.

In the same vein, a subjective norm which is regarded as a social pressure felt by the potential users to perform or not to perform a given behaviour was discovered as a positive significant factor that influences users' behaviour toward the adoption of a given technology. Subjective norm was examined by Wheatley and Hervieux (2019) and they all found it to be a good determining factor that positively influences users' behaviours toward adopting technology. Subjective norm measures how others in society consider a given behaviour, which leads to evaluating the behaviour in question as acceptable or rejectable (Ajzen, 2020). Subjective norm has been emphasized as a good factor influencing the intention to use or perform a certain behaviour (Momani & Jamous, 2017).

Behavioural intention which is cited as the motivational factor in the TPB plays a significant role in influencing behaviour (Momani & Jamous, 2017). The higher the intention of users to carry out certain behaviour the strong likelihood they have to perform such behaviour (Wolitski & Corby, 2015). Hayani et al. (2021) acknowledged the robustness of subjective norm in influencing the intention to use novel technology. The most important factor that determines the behaviour is intention. An individual's perceived possibility that they would engage in action is referred to as intention (Kan et al., 2020).

Based on the aforementioned, this research proposes that:
H1: Attitude will influence the use of AI positively in Academic libraries
H2: Subjective norm will influence the use of AI positively in Academic libraries
H3: Perceived behavioural control will influence the use of AI positively in Academic libraries

Research Model for Predicting and Understanding Intention to Use AI

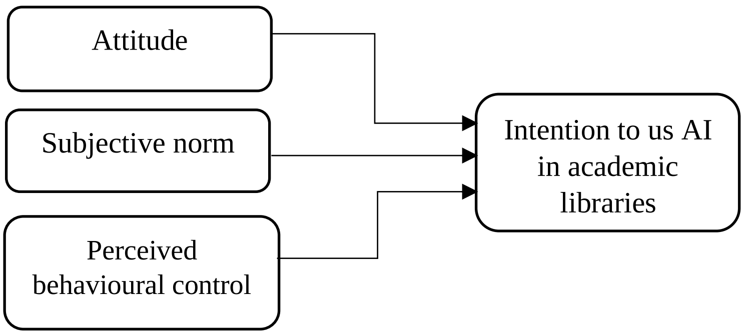

Figure2: Research Model

The above model (See figure 2) is developed to understand and predict the intention to use AI among librarians. The model which was developed from the theoretical lenses of TPB would be able to further justify the powerfulness of TPB toward determining intentions to act and eventually act based on some influencing variables. Attitude, perceived behavioural control and subjective norm variables are meant to predict and understand the intention of librarians toward acceptance and use of AI in their daily library operations. Therefore, this research assumes that the theoretical ideology of TPB could be used to guide the processes of intention to use AI by librarians in academic libraries, hence address objective 3 of this research.

Methodology

Research Design

A quantitative approach using a cross-sectional design was adopted for this research. Cross-sectional survey approach is mostly used in such related research because it allows collection of data across a sample population at a specific point in time (Yakubu *et al.*, 2021). Therefore, this research data was collected within a given period of one month.

Instrument of Data Collection

A structured questionnaire which was prepared using previously verified scales was used as an instrument for data collection. The first part of the questionnaire contained demographic information of respondents while the second part contained questions based on the study variables. A 7-point Likert scale was adopted in measuring the variables using 1- as strongly disagree and 7- as strongly agree. In oder to get good sample opinion, 7-point Likert scale was seriously recommended over 5-points (Likert, 1932; Schreiber, 2021)

Population and Sample of the Research

242 Professionals and paraprofessionals librarians in the selected universities libraries comprise the population of the study and a minimum of 119 samples of respondents were estimated using the G*Power application for sample estimate. A proportionate stratified random sampling technique which involved drawing samples randomly from the groups in proportion to each group population (Saunders *et al.*, 2009) was adopted for the distribution of the questionnaire; in which 157 were distributed across the three selected academic libraries out of which 151 were successfully returned and analysed.

Method of Data Analysis

The returned questionnaires were screened before being subjected to reliability and validity tests. Interestingly, their validity and reliability values satisfied the required threshold. Data for the research was analysed using Statistical Package for Social Science (SPSS) version 20 and Partial Least Square – Structural Equation Modelling (PLS-SEM). All descriptive analyses were carried out using SPSS while model evaluations are done using PLS-SEM.

Results

Characteristics Information of Respondents

This section revealed the clear pictures of the respondents who participated in the research. All their characteristics information tells the reader who and how they are. The following table (Table 1) shows the characteristics information of respondents.

Table 1: Characteristics Information of Respondents

Demographic variable	Item	Frequency	percentage
Gender	Male	117	77.5
	Female	34	22.5
Qualification of respondents	PhD	2	1.3
	Masters	42	27.8
	Degree/HND	60	39.7
	Diploma/NCE	31	20.5
	Others	16	10.6
Respondents' years of experience	1 – 5	4	2.6
	6 – 10	15	9.9
	11 - 15	51	33.8
	16 – 20	52	34.4
	21 – above	29	19.2
Knowledge about AI	Do you have little knowledge about AI	151	100

From the characteristic information of respondents as indicated in Table 1, findings revealed that the majority of respondents are male represented by 77.5% while their female counterparts constituted the minority represented by 22.5%. This finding coincided with other previous findings related to this research (Edwin, 2018; Kayode et al., 2020) while it contradicted other previous findings related to this research (Oliveira et al., 2014). Similarly, findings on the qualifications of respondents revealed that 1.3% had a PhD, 27.8% had masters, 39.7% had a Degree/HND, 20.5% had a Diploma/NCE and 10.6% had other qualifications not mentioned here. This finding indicated that the majority of respondents are Degree/HND holders while the minority of them are PhD holders. This further illustrated that most of the respondents who participated in this research are well-educated, hence would like to use artificial intelligence to deliver services to library patrons. In the same vein, respondents' years of experience results revealed that 1-5 years had 2.6%, 6-10 years had 9.9%, 11-15 years had 33.8%, 16-20 years had 34.4% and 21 - above years had 19.2%. This has indicated that the majority of the respondents are well-experienced librarians that can handle and utilise artificial intelligence tools very well. Findings of respondents' artificial intelligence knowledge revealed that all the respondents testified that they have little knowledge about artificial intelligence. This is not surprising as the majority of them have higher qualifications and a good number of years in library services.

T*he Extent of Librarians' Intention to Use A I in the Academic Libraries*

The extent of librarians' intention toward the adoption of artificial intelligence in academic libraries has been examined to address objective 1. Interestingly the findings revealed that the librarians under study have shown great intention to use artificial intelligence (AI) in their libraries. This can be seen from the descriptive statistics of their responses where the mean value for that "the extent of librarians' intention toward the adoption of artificial intelligence in the academic libraries" is 4.675 out of 7. It should be noted that the intention variable was measured using a 7-points Likert scale ranging from 1- Strongly disagree to 7- Strongly agree. Therefore, the 4.675 mean value of the intention variable signified high intention to use the AI by the librarians, hence objective 1 is addressed.

Table 2: Extent of Librarians' Intention to Use AI in the Academic Libraries

	N	Minimum	Maximum	Mean	St. Dev.
ATT	151	1.60	6.80	4.307	1.244
SUBNO	151	1.60	7.00	5.386	1.193
PBC	151	1.80	7.00	5.262	1.222
INT	151	3.00	6.80	**4.675**	0.956

ATT= attitude, SUBNO= Subjective Norm, PBC= Perceived Behavioural Control, INT= Intention

Measurement Model Evaluation

The first thing that a researcher needs to do after screening the data in Partial Least Square-Structural Equation Modelling (PLS-SEM) is to conduct measurement evaluations and ensure that all the constructs and their items are reliable and valid before conducting Model evaluation (Hair et al., 2014). Based on that, the validity and reliability of the instrument and constructs are carefully evaluated and ensure that they meet the necessary minimum threshold.

Validity highlights the accuracy of measures used or it indicates the extent to which a given concept is acutely measured in research. In evaluating the validity, both discriminant and convergent validity of the items and constructs are evaluated. Discriminant validity reveals how measures that are supposed to be different have empirically differed and convergent validity reveals how constructs that are supposed to be related are in fact empirically related (Cheah et al., 2018). To establish convergent validity as recommended by (Hair et al., 2017; Hair et al., 2011; Ramayah et al., 2018), the loading factor must have at least a value of 0.5, Average Variance Explain (AVE) must have a minimum threshold of 0.5 while composite reliability (CR) and Cronbach alpha (CA) values must not be less than 0.7. Interestingly all the required threshold values are achieved which signified the establishment of reliability and convergent validity as can be seen in Table 3. It should be noted that items ATT4 and INT2 were deleted due to the low loadings they exhibited.

Table 3: Reliability and Convergent Validity Evaluation Using Items Loadings, AC, CR and AVE

Variables	Items	loadings	CA	CR	AVE
ATT	ATT1	0.798	0.872	0.906	0.707
	ATT2	0.844			
	ATT3	0.858			
	ATT5	0.862			
SUBNO	SUBNO1	0.801	0.801	0.851	0.535
	SUBNO2	0.753			
	SUBNO3	0.621			
	SUBNO4	0.802			
	SUBNO5	0.661			
PBC	PBC1	0.861	0.755	0.830	0.505
	PBC2	0.829			
	PBC3	0.745			
	PBC4	0.549			
	PBC5	0.490			
INT	INT1	0.672	0.745	0.838	0.566
	INT3	0.750			
	INT4	0.839			
	INT5	0.737			

CA=Cronbach Alpha, CR=Composite Reliability, AVE= Average Variance Explain, ATT= attitude, SUBNO= Subjective Norm, PBC= Perceived Behavioural Control, INT= Intention

Moreover, to establish discriminant validity, Leguina (2015), Hair et al. (2011) and Memon et al. (2017) proposed three measurements to be used which include cross-loadings, Fornell Larcker criterion and heterotrait-monotrait ratio. However, Cheah et al. (2018) and Henseler et al. (2015) specifically recommended the use of the heterotrait-monotrait ratio as the best option. Based on that, this research evaluated and established discriminant validity using the best option which is a heterotrait-monotrait ratio (HTMT). HTMT ratio measures the average correlations of the items across constructs (Henseler et al., 2015). Interestingly the minimum threshold values of the constructs for the establishment of convergent validity are achieved by having values of less than 0.90 each (Henseler et al., 2015, 2016). All the HTMT values recorded by ach construct are < 0.90 which depicts the presence of discriminant validity because HTMT value closer to 1 indicate a lack of discriminant validity among the constructs (Leguina, 2015)

Table 4: Discriminant Validity Evaluation Using Heterotrait-Monotrait Ratio

	ATT	INT	PBC	SUBNO
ATT				
INT	0.669			
PBC	0.18	0.659		
SUBNO	0.289	0.643	0.403	

ATT= attitude, SUBNO= Subjective Norm, PBC= Perceived Behavioural Control, INT= Intention

Structural Model Evaluation

The structural model evaluation deals with estimating some important parameters that include the path coefficient for testing hypotheses, effect size (f^2) of each independent variable, coefficient of determination (R^2) and predictive relevance of the model (Q^2). This research evaluated all the mentioned parameters based on the previously established rule of thumb recommended by (Hair et al., 2019; Ramayah et al., 2018).

Path coefficient which indicates the significant relationships between the research independent variables and the dependent variable was examined using t-values and P-values. The results revealed that all three independent variables (attitude, subjective norm and perceived control behaviour) positively influenced the dependent variable (intention to use Artificial intelligence in the selected academic libraries) implying that objective 2 is achieved. The threshold values for T-values using one-tailed is 1.645 and above, whereas the p-values must not be greater than 0.05 at 95% confidence (Hair et al., 2017; Sarstedt et al., 2014). Interestingly all the constructs' relationships recorded T-values above 1.645 and p-values below 0.05 respectively which signified that the independent variables can influence the intentions of librarians to use artificial intelligence in their respective academic libraries. Therefore, all the three hypotheses are accepted and research objective 2 is addressed. Table 5 presented the path coefficient results.

Table 5: Path Coefficient of Determination Showing the Mean, St. Deviation, T-values and P-values

Relationships	Hypotheses	Mean	ST.DEV	T-values	P-Values	Decision
ATT -> INT	H1	0.452	0.052	8.616	0.000	Accepted
PBC -> INT	H2	0.395	0.050	7.838	0.000	Accepted
SUBNO -> INT	H3	0.301	0.052	5.739	0.000	Accepted

ATT= Attitude, PBC= Perceived Behavioral Control, SUBNO= Subjective Norm, INT= Intention

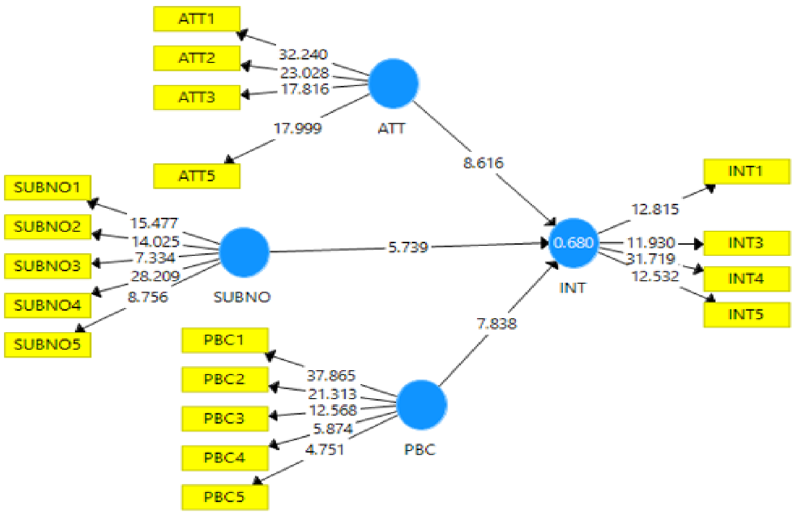

Figure 3: Pictorial representation of t-values and coefficient of determination (R^2) as revealed by PLS-SEM output.

Furthermore, R^2, F^2 and Q^2 were equally evaluated as mentioned earlier. R^2 explains the variances that are accounted for by the dependent variable as a result of the collective contribution of the independent variables (Leguina, 2015). The R^2 values of 0.25, 0.50 or 0.75 are considered small, moderate and large respectively (Hair et al., 2013). This research's R^2 recorded 0.680, implying that 68% of variances are accounted for in the dependent variables by the independent variables, which is moderate enough. On the other hand, F^2 explains the variances accounted for in the dependent variable by each individual independent variable. F^2 values of >= 0.02, >=0.15 and >= 0.35 are considered small, moderate and large respectively (Cohen, 1988). This research's F^2 for ATT, PBC and SUBNO recorded the values 0.548, 0.415 and 0.222 respectively; implying that each of the independent variables (ATT, PBC and SUBNO) has a good effect on the dependent variable (intention to accept AI). Moreover, Q^2 measures whether a model has predictive relevance or not (Leguina, 2015). Q^2 values greater than 0 indicates that the model has predictive relevance (Chin, 1998; Cohen, 1988). Q^2 of this research is achieved by having a value of 0.354, implying that the model is good by having a moderate predictive relevance and hence can accurately predict the targeted variable (intention to use AI by librarians). This addresses objective 3 of this research. Therefore, as indicated in Table 6, both the R^2, F^2 and Q^2 satisfied the required threshold suggested by (Chin, 1998; Hair et al. 2011; Hair et al. 2017) and signified the achievement of objective 3 of this research.

Table 6: Coefficient of Determination (R^2), Effect Size (F^2) and Predictive Relevance (Q^2) Results

Constructs	F^2	Effect	R^2	Effect	Q^2
ATT > INT	0.548	High effect	0.680 (68%)	Moderate	0.354
SUBNO > INT	0.222	Moderate effect			
PBC > INT	0.415	Moderate effect			

ATT= Attitude, PBC= Perceived Behavioral Control, SUBNO= Subjective Norm, INT= Intention

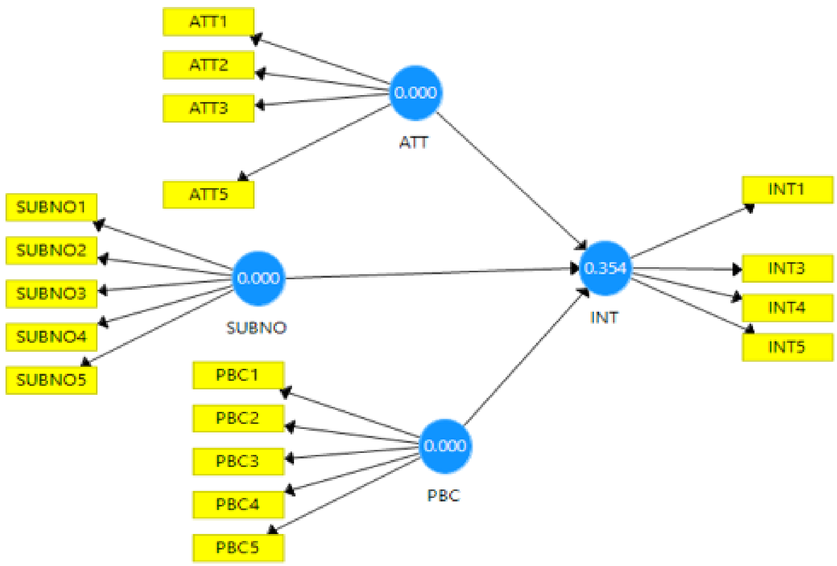

Figure 4: Pictorial representation of Predictive Relevance (Q^2) as revealed by PLS-SEM output.

DISCUSSION

This finding has both theoretical and managerial implications. Theoretically, a model for predicting and understanding the librarians' intention to use Artificial intelligence (AI) was developed which was extremely scarce or absentespecially in North-eastern Nigerian academic libraries context. Managerially, this finding will provide a guide to librarians, university management, government and other relevant stakeholder in the librarianship on what can influence potential users' intention to use AI for delivering a better, faster and efficient services to library patrons.

ATT (H1, t= 8.616, p= 0.000) is found to be a significant determining factor of intention to use Artificial intelligence (AI) by librarians, hence proved the acceptance of hypotheses 1. This implied that ATT is a factor that can influence the intention of librarians to use AI in delivering their services to library patrons. Attitude toward AI can lead to the use of the AI by librarians. This study finding really emphasized that respondents testified the robustness of good attitude toward influencing the potential user's intention to use AI in their libraries. This finding supported findings of Pourmand et al. (2020), Kumar et al. (2019) and Wolitski and Corby (2015) who found that ATT is a factor that positively influence the behavioural intention to use novel technology or act on a given action. However, the finding contradicted that of Gaston and Gerjo (1996) who discovered that ATT is not always influencing the use of novel technology such as AI.

In the same vein, this study finding found that SUBNO (H2, t= 5.739, p= 0.000) has a direct positive effect on the intention to use AI by librarians which implied that hypotheses 1 is accepted. This study's finding suggests that librarians will be determined to use AI once they are influenced by the members of the community who have been using it. The respondents explicitly signified the powerfulness of other users' influence on potential users of AI. Therefore, this study takes a stand that SUBNO is a vital and positive determinant that influences the librarian's intention to use AI in giving out services to library patrons. This study finding coincided with previous finding who found the robustness of SUBNO in influencing the potential user's intention to use new technology and to act on given action (Gaston & Gerjo, 1996; Hagger et al., 2002; Kan et al., 2020; Wolitski & Corby, 2015). However, it (the finding) contradicted that of Arpaci (2016) who found that SUBNORM does not influence intention to use a technology.

On the same track, PBC (H3, t= 7.838, p= 0.000) is found to be a significant factor that positively influences the librarians' intention to use AI to provide services to library patrons, which therefore signified that H2 is accepted. This study finding implied that PBC influences the intention of potential users of AI to use it for delivering services. The finding further suggests that once librarians realized that they have controls over what it can lead them to use AI, they can burst their intention toward the acceptance and use of the AI in their respective libraries. Based on this study's findings coupled with many extant studies, PBC is regarded as a useful, strong and positive determinant that influences the librarians' intention to use AI for delivering services to library patrons. The finding also supported that of Wolitski and Corby (2015), Kan et al. (2020) and Siqueira et al. (2022) who emphasized the positive significance influence of PBC on the intention to use a novel technology. However, differs with the finding of Arpaci (2016) who revealed that PBC did not influence a behaviour to act on certain function.

CONCLUSION

Despite the bunch of benefits that AI offers to users, especially academic librarians, its usage in the libraries became matter of serious concern due to its non-utilization by librarians. This research therefore exposed some of the factors that can influence the intention of the librarians to accept and use such innovative technology (AI) in order to burst and offer better, simple, efficient and all the time services to library patrons. The influential factors just identified are to be fully considered by the librarians and other relevant stakeholders in the library ecosystem when making intention to use AI. Furthermore, a model for predicting and understanding the intention to use the AI was developed and need to be equally considered when trying to make an intention to use AI. This research to some extent provides a blue print that can be used and simplify the processes of approaching the use of AI in the academic libraries of North-eastern Nigeria and beyond.

The number of theoretical predictors which are only three and the scope of the research which is the university library in Northeastern Nigeria limited this research to some extent. Therefore this research recommended that future research should include all categories of educational institutions' libraries, the scope of the geographical zones should be beyond North-eastern Nigeria, more theoretical predictors should be used and the need to figure out a single AI tool such as robotic, chatbots, virtual reference assistant, pattern recognition etc for investigation.

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