

The Relationship between Artificial Intelligence (AI) Quality, Customer Preference, Satisfaction and Continuous Usage Intention of e-Banking Services

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Abstract

This study was set to examine the relationship between artificial intelligence (AI) quality, customer preference, satisfaction and continuous usage intention of e-banking services powered by AI solution. To achieve this, a cross-sectional research design was employed to collect data from the bank customers using purposive snowball sampling. In total 274 responses were retrieved from the bank customers that agreed to participate in the study and 246 were useful for the final data analysis. Analysis was done using partial least square structural equation modeling (PLS-SEM) approach with aid of SmartPLS 3.2.8. A snowball non-probability sampling procedure was used for the data collection. The findings indicate that the AI quality have a positive effect on satisfaction and satisfaction has significant positive effect on the intention of continuing use of e-banking services. However, consumer preference was not significantly related to continuous usage intention of e-banking services. This is practically possible in Nigerian context. Because we observe that majority of the respondents does not have specific preference of using or interacting with e-banking services powered by AI as against those control by human interactions. The implication of this findings is that is the used of AI based services in the Nigerian context is still at it infancy level. Therefore, there is still much to learn from the experience of both planners, implementers and beneficiaries. This study is perhaps, the first of its kind to examine the relationships of AI chatbot quality on customer satisfaction and continuous usage intention of e-banking services. It is therefore, contributes to the development of literature in this direction.

Keywords: Artificial intelligence quality, preference, satisfaction, continuous usage intention, e-banking service.

Introduction

Nigerian banking sector experienced radical transformation to increase speed, quality and flexibility of the financial services delivery through IT capabilities (Ringim, 2012; Dantsoho, 2016; Dantsoho & Ringim 2016). As a result, some of the leading Nigerian banks employed Artificial intelligence (AI) chatbot service solution to improve their e-banking service experience. A typical example of the AI system includes Tamata and Ada for Access and Diamond Bank, as well as Sami for Stanbic IBTC's and Leo for the UBA bank. Whereas, some banks are still contemplating of joining the technological transformation through the use of AI chatbot, other banks has gone beyond a simple implementation of AI chatbot to solve front office operational problems but also linked to bank end office operations. However, customer's experience about AI in the banks is that of "AI chatbot" the focus of the study is on the quality of chatbot powered by AI which banks used to implement effective and efficient customer service delivery. Therefore, these AI chatbots such as Leo are very sophisticated, expensive and will likely to offer a more delightful customer experiences than others. However, despite substantial breakthroughs in the AI implantation for the financial service delivery, little work examined under what conditions AI quality and preference lead to continuous usage intention of the e-banking services (Accenture, 2019; Deloitte 2019; Xie, 2019). The issues of quality and continuous usage intention of IT-enabled services investigated in the information systems (IS) research revealed a varying degree of findings. Among of these findings is that the relationship between quality, preference and satisfaction is complex. Whereas a number of scholars have tried to simultaneously identify the relationships between these constructs and measure their magnitude (Keisidou et al., 2013; Jan & Abdullah, 2014).

In the banking sector, past studies have argued on the understanding of the relationship between the satisfaction construct, its antecedents and consequences due to its importance in explaining consumer experience and continuous usage intention (Ladeira, Santin & Araújo, 2016). More so, there is submission that customer satisfaction does not necessarily lead to continuous usage of a particular product or services. Therefore, there exist a scanty study on the relationship between quality, consumer preference, satisfaction and intention of continuing use of Artificial intelligence (AI) app. Also it is not certain whether satisfaction could mediate the relationship between AI system quality and continuous usage intention particularly in the multicultural context of Nigeria. Hence, the objective of the study was to investigate the relationship between the AI quality, preference, satisfaction and continuous usage intention of e-banking services from the African perspectives.

To develop a better understanding of how AI quality attributes, affect continuous usage intention through satisfaction adoption in response to digital disruption, we first clarify conceptual definitions of the research construct, illustrate the role of preference and then focused on the banking as competitive intensive industry to collect data directly from the customer for our research model. To achieve this, three research questions are addressed: Does AI quality influence user's satisfaction and continuous usage intention of e-banking services? Does customer preference on information system (IS) influence perception of Ai quality? Does

Satisfaction mediate the relationship between AI quality and continuous usage intention? The rest of the paper is presented as follows. It starts with the theoretical framework for the study, followed by hypotheses development. Methodology of the study which described research study designed to test the research model. It finally presents the results, implications, limitations and conclusions of the study.

2. Theoretical Framework and Hypotheses Development

Research on artificial intelligence begun in 1950s when scientists used computer as a revolutionary tool to stimulate and exhibit intelligence (Simon, 1995). From its birth, AI foundation was based on ability to build a system that exhibits some kind of intelligence similar to that of human intelligence in terms of numerical analysis, natural language processing and facial recognition and so on. Today, there are various form of chatbots dominates the market with different functionalities and the choice depend on preference and experience. Whereas a rule based chatbot has limited capability, it only understands a pre-defined set of options, a chatbot powered by AI understand user's intent and context of the user's conversation and therefore is capable of bringing differential benefits. These chatbots are assumed to be an advanced type of chatbot powered by AI and thus the focus of this study, not the less complex chatbot with pre-defined features and limited capability.

In addition, there is insinuation among the industry leaders and researchers that the use of chatbot to offer financial services across the countries, have failed to deliver a seamlessly, delightful and user experiences in the virtual environment (Olsson, 2017; van Lun 2018). Specifically, Van Lun (2018) asserts that majority of the chatbots in the maker lack intelligence by getting stuck and not knowing what to do, and the lack of connectivity with the backend office operations. Shah (2017) argued that firms that rush into IT investment for virtual interaction will likely to go into rule-based chatbot and if that happened they will be leaving out for the AI capabilities for their chatbots.

The service quality has been described to mean the overall customer's judgment about firm's excellence or superiority in service (Zeithaml, 1987) based on overall evaluation of the customers. Merchman and Verleye (2019) argue that the issue of quality as conceptualized in the service marketing literature and as measured by a quality model for chatbots involves perceived quality. Also, review of several empirical studies that examined consumers' preference of internet banking services across the countries indicates lack of consensus on the determinants of consumer acceptance (Ezzi, 2014). However, Bolar (2014) identified technology interface as most preferred factors for using e-transaction. In Malaysia, consumers indicates awareness ease of use, security and trust as the determinant of e-banking adoption (Al-Fahim, 2013). Al-Fahim (2013) also argued that Malaysian does not have problem with those factors since they have sufficient knowledge on e-banking services. This differ with that of Nigeria where digital banking was recently introduced (Financial stability, 2017). To understand how preference influence AI quality acceptance, satisfaction and continuous usage intention of e-banking services the study hypothesised the following.

H.1 There is significant relationship between preference and perceived AI system quality.

H2 Preference has significant effect on satisfaction of e-banking services powered by AI system.

H3 Preference is significantly related to Continuous usage intention of e-banking services.

As regard to evaluation of the AI quality on satisfaction, and continuous usage intention of e-banking services. Some scholars are of the view that chatbots offer a service similar to the mobile application offered by firms and these models (Wang, Ou & Chen, 2019) can be used to evaluate chatbot quality. On the other hand, some researcher argue that service consumers expect different thing from chatbot in comparison with tradition mobile app (Merchman & Verleye, 2019). More so, in the evaluation of the service of quality AI, at least the three well-known service quality attributes in the existing literature; should be considered. These characteristics include intangibility and heterogeneity as well as inseparability of service offering from production stage to consumption (Upah 1980; Booms & Bitner, 1981; Zeithaml, 1981). These made service offering to be inconsistent and service performance depends on multiple factors (Merchman & Verleye, 2019). With increasing industry competition, customer sophistication and changing regulations (Deloitte, 2019). It has been suggested that banks that are using AI chatbots should typically assess them based on the quality of user satisfaction (Singh, 2017). Kumar and Dash (2013) reported that perceived service quality is as important predictor of consumer satisfaction and retention in the Indian banking sector. Hence, as satisfied customers tend to have higher degree of service usage (Ram & Jung, 1991), possess stronger repurchase intention (Tan, 2010). This is strategically important, since in the virtual environment there is little means of differentiating one offering from other. When customer loyalty become obsolete excellence in service quality emerge as the alternative means of value addition. Consequently, the following hypotheses are employed in the study.

H4 Perceived AI quality has significantly influence customer satisfaction of e-banking services.

H5. There is significant relationship between AI system quality and continuous usage intention.

H6. Satisfaction mediates the relationship between AI system quality and continuous usage intention.

Conceptual Model

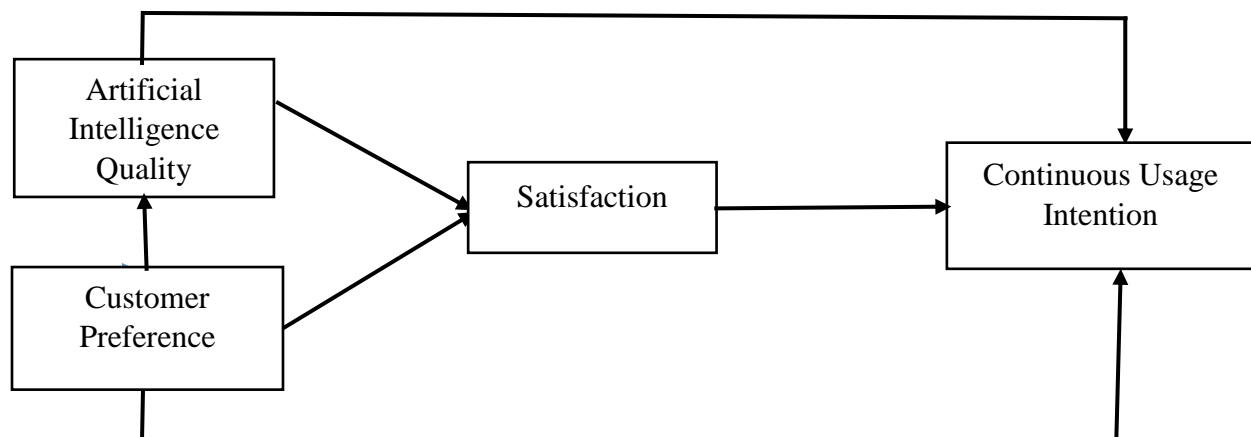


Figure 1. the proposed model

With the increased use of internet and other e-banking services scholars begins to explore the factors that determine the adoption or acceptance e-banking services and subsequent users behaviour. One theoretical lens that dominate scholars' discussion is the information system (IS) success model (DeLone & McLean, 1992; 2003), the Ajzen's model of Theory of Planned Behavior (TPB) (Ajzen 1985) and Technology Acceptance Model (TAM) (Davis, 1989) which scholars have found to be a strong predictor of consumer behavioral intention (Mardiana, Tjakraatmadja & Aprianingsih, 2015). However, as existing literature shows that only perceived usefulness (PU), performance expectancy, effort expectancy (EE), and social influence (SI) that significantly predict behavioral intention (Mardiana et al., 2015), unified theory of acceptance and use of technology (UTAUT) was included to explain the role of preference on continuous usage intention.

3. Methodology

To achieve this objective, cross-sectional research design was employed to collect data from the bank customers using purposive snowball sampling. In total 274 responses were retrieved from the bank customers that agreed to participate in the study and 246 were useful for the final data analysis. Analysis was done using partial least square structural equation modeling (PLS-SEM) approach with aid of SmartPLS 3.2.8 (Ringle, Wende, Sven & Becker, 2015). Snowball sampling non-probability sampling procedure was used for the data collection. Respondents include people from all work of life ranging from postgraduate students, working people and retirees. Data were collected from the three popular northern states of Abuja, Kaduna, Kano and few from customers in Lagos and Port Harcourt which covered all the four geographical zones in the country. For measurement of the constructs; Artificial intelligence quality was measure using 9 items (Lee & Lee, 2009) Preference was measured using 5 items (Lee & Lee, 2009; Muthitharoen, Palvia & Grover, 2011). Likewise, satisfaction, continuous usage intention were measured 5 and 4 items respectively (Cronin, Brady & Hult, 2000; Zheng, Zhao & Stylianou, 2013). A 5 point Likert scale was used instead of 7point Likert scale, with 1 strongly disagree, and 5 strongly agree. This gives respondents more balance options among the two extreme end, and neutral option at the center of the scale.

Considering the fact that data were collected from the research respondents at various locations both procedural and statistical methods have been used to check and minimise the occurrence of common method bias. On the procedural method, a clear instruction on how to complete the survey the questionnaire was given to respondents. The anonymity and confidentiality of the research participants was first assured before the embarked into filling the questionnaire (Podsakof MacKenzie & Podsakoff, 2003). The questionnaire statement were pretested to avoid confusion and unnecessary difficulties in answering the questions (Reio, 2010). The respondent were also informed that there is no right or wrong answers the researcher is only interested in knowing their honest opinion (Schwarz, Rizzuto, Carraher-Wolverton, Roldán, & Barrera-Barrera, 2017). On the statistical methods, the Harman's single-factor was used test to examine the issue of common method variance (Lindell & Whitney, 2001; Podsakoff & Organ, 1986). Using principal components factor analysis, the result reveals 23 with first factor accounting for

only 22% variance and there is no general factor in the unrotated factor structure. Hence, it is safe to assume that common method bias is not an issue in the current study and therefore, appropriate to proceed with analysis.

4. Data Presentation and Analysis of findings

This study utilise the variance-based Structural equation modelling (SEM) analysis through help of SmartPLS 3.2.8 statistical software (Ringle, Wende & Becker, 2015). In the First stage, the study assessed the measurement model and then the structural model (Chin, 2010; Sarstedt et al., 2017). The result of the PLS algorithm for measurement model evaluation is presented in figure 1.

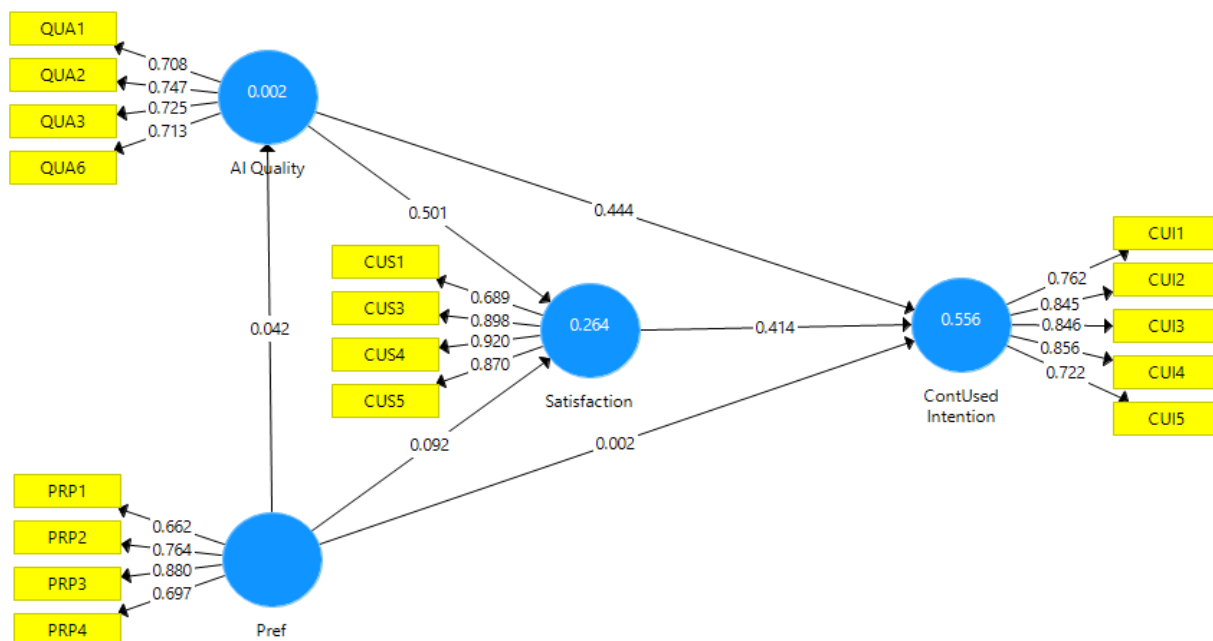


Table 1. *Measurement Model Validation.*

Construct/Item	Loading	Composite reliability	Average Variance extracted
Continuous Usage Intention		0.903	0.653
CUI1	0.762		
CUI2	0.845		
CUI3	0.846		
CUI4	0.856		
CUI5	0.722		
Satisfaction		0.911	0.721
CUS1	0.689		
CUS3	0.898		
CUS4	0.920		
CUS5	0.870		
Preference		0.840	0.570
PRP1	0.662		
PRP2	0.764		
PRP3	0.880		
PRP4	0.697		
Artificial Intelligence Quality		0.814	0.523
QUA1	0.708		
QUA2	0.747		
QUA3	0.725		
QUA6	0.713		

The assessing measurement model starts with evaluation of individual item reliability through indicator loadings of 0.7 as indication good reliability and 0.6 are also considered accepted for in an exploratory research (Hair et al., 2017). As can be seen in Table 1 indicators loadings for the items in the research model are within the accepted benchmark of 0.6 and above for the exploratory study.

The second of step of establishing quality criteria for the measurement model is that of internal consistency reliability using composite reliability (Jureshag 1971). In Table 1, a reliability values from 0.6 to 0.7 are considered acceptable for exploratory research and 0.7 to 0.9 indicates satisfactory good reliability (Hair et al., 2014). However, CR value of 0.95 are problematic as such indicates redundancy thereby reducing construct reliability (Diamantopolous, et al., 2012). It may also indicate undesirable response such as straight lining from the respondents (Hair et al., 2017).

The third step in the assessment of the measurement model is convergent validity (CV) diagnosis. Convergent validity is the extent to which the construct converge in order to explain the variance of its items (Hair et al., 2012). Therefore, the criteria for measuring CV is the average variance extracted (AVE) for all the items for each construct (Hair et al., 2017). Under this, the minimum accepted AVE is 0.5 or higher (Hair et al., 2012). That is an AVE of 0.5 or higher indicates that the construct explains 50% or more of the variance of the items that make

up the construct (Hair et al., 2017). As can be seen in Table 4.1 all the construct AVE is within the benchmark of 0.5 and above.

The fourth step under measurement model validity assessment is the analysis of discriminant validity (DV). DV is the extent to which a construct is empirically distinct from other construct in the structural model (Hair et al., 2017). DV was established the use of Hetrotrait Monotrait (HTMT) which has been considered to be superior to both cross-loadings and Fornell and Lacker criteria (Henseler, et al., 2015). The advantage of HTMT ratio of the correlation it takes the serial mean of the item correlation against the construct correlation (geometric mean) as cited (Hair et al. 2017). The threshold values of establishing HTMT should be less than or equal to 0.85 (Henseler et al., 2015) and 0.90 as suggested (Franke & Sartedt, 2019). As can be seen in Table 4.2 the DV is established as the serial mean of all the construct is below the lower benchmark of 0.85.

Table 2. *Discriminant Validity HTMT*

Construct	AI Quality	CU Intention	Preference	Satisfaction
AI Quality				
CU Intention	0.813			
Preference	0.075	0.073		
Satisfaction	0.630	0.724	0.131	

The first step to evaluate structural model is to start with structural model collinearity diagnosis to make sure it does not bias the structural model result. Under this the variance inflation factor (VIF) are used to assess the collinearity among the construct and VIF above 5 are considered to be a problem as it indicates collinearity (Hair et al., 2017). The result for collinearity diagnosis shows that collinearity is not an issue as the VIF values for all the research constructs ranged from 1.34 to 1.36.

The next step is to assess the size and significance of path coefficients to test the hypothesizes. The closer the path coefficients values are to the 1 the stronger they are in predicting the target construct (Hair et al., 2020). The result of the size and significance of path coefficients is seen in Table 4.1.

Table 4.1. *The size and significance of path coefficients*

Hypotheses	Beta	(STDEV)	T Statistics	0.025	0.975	Support (Hypotheses)
H1. Pref -> AI Quality	0.042	0.069	0.611*	-0.129	0.163	No
H2. Pref -> Satisf.	0.092	0.048	1.909*	-0.010	0.183	No
H3. Pref -> CUI	0.002	0.038	0.061*	-0.075	0.075	No
H4. AI Qual -> Satisf	0.501	0.041	12.23***	0.420	0.582	Yes
H5. AI Qual -> CUI	0.444	0.042	10.515***	0.360	0.528	Yes
H6. Satisf -> CUI	0.414	0.050	8.305***	0.315	0.511	Yes

*** $P < 0.001$, ** $P < 0.05$, * $P < 0.10$ (two-tailed test)

Recalled that H1, H2 and H3, are on the relationship between preference to perceived AI quality, preference to satisfaction and lastly preference to continuous usage intention and the bootstrapping result produced beta values ($b = 0.042$, $t = 0.611$, $p > 0.05$, $b = 0.002$, $t = 0.061$, $p > 0.05$, $b = 0.042$, $t = 0.611$, $p > 0.05$) respectively. On the other hand, H4, H5 and H6, were on the relationship between AI quality to satisfaction, AI quality to continuous usage intention and lastly satisfaction to continuous usage intention. The result produced beta values ($b = 0.501$, $t = 12.230$, $p < 0.001$, $b = 0.444$, $t = 10.515$, $p < 0.001$, $b = 0.414$, $t = 8.305$, $p > 0.05$) respectively. Hence, hypotheses 1, 2 and 3 are not supported while hypotheses 4, 5, and 6 are supported. Overall the result reveals that satisfaction mediates the relationship between AI quality and continuous usage intention of e-banking services.

To verify whether the relationships between constructs are truly significant or not, we can also examine the confidence interval by using both the lower and upper bound values and if the lower bound shows a sign of negativity (0) it simply indicate that the relationship is not truly significant despite the presence of p-value and t-statistics (Wood, 2005). This analysis is also present in Table 4.2.

The third step is to evaluate the coefficients determination using the R^2 value which measure the variance explained in each of the dependent construct. R^2 is therefore a measure of model explanatory power (Shmulei & Koppins, 2011). The R^2 value ranged from 0 to 1 with higher value indicating a greater explanatory power (Hair et al., 2017). Based on the rule of thumb an R^2 value of 0.70, 0.50 and 0.25 can be considered as substantial, moderate and weak R^2 value (Henseler et al., 2009). However, in some disciplines an R^2 value of 0.10 is considered acceptable (Falk & Miller, 1992). More so, Hair et al. (2010) argue that the accepted level of R^2 dependent on the context to which the research is carried out. The result from the PLS algorithm in figure 1, return an R^2 value of 26% for the relationship between preference and AI quality on satisfaction and R^2 value of 56% for the overall mediation model. The result reveals that AI quality and preference together explain 26% of the variance in the satisfaction. As per Henseler et al., (2009) benchmark the obtained R^2 value is moderate. More so, the variance explains in the overall mediation model by all the research constructs can be considered as substantial (56%) as suggested (Henseler et al., 2009).

The fourth step is to examine the effect size (f^2) to establish if the R^2 values change if a construct is omitted from the model. It is known as an error of omitting a particular construct (i.e. exogenous construct) in the research model (Cohen 1988). As a rule of thumb, Cohen (1988) suggested that values ranging from 0.2, 0.15 and 0.35 indicates small, medium and large effect size. The result of f^2 statistics reveals that AI quality would have from moderate to substantial effect on both satisfaction (f^2 ; 0.34) and continuous usage intention (f^2 ; 0.33) as the mediating and variable respectively. Likewise, omitting satisfaction would have a moderate effect (f^2 ; 0.29) on dependent variable. However, preference that does not significantly related to the continuous usage intention have also not indicated any change in R^2 on both mediating and dependent

variables. This result mean that removing both AI quality and satisfaction would result in the substantial change in R^2 value, and this clearly indicates the strategic role of customer satisfaction on continuous usage intention.

To examine the overall model fitness, this study employed the Standardized Root Mean square Residual (SRMR), which was used to measures model fitness (Henseler et al., 2014). Under this a value of zero indicates perfect fit, and any value less than 0.10 or of 0.08 is generally considered acceptable as a good fit (Hu & Bentler, 1999). The result of analysis (Table 2) returned an SRMR value of 0.070 which is also within the accepted threshold value of .08 indicating a very good fit.

Table 2. Overall Model fit

	Saturated Model	Estimated Model
SRMR	0.070	0.070
d_ULS	0.758	0.758
d_G	0.251	0.251
Chi-Square	565.317	565.317
NFI	0.819	0.819

Next, the cross-validated redundancy value (Q2) was used to examine the predictive relevance of the model. The fifth step is to examine the structural model predictive relevance through the Q2 value of the in sample prediction (Geissier, 1974) The guideline for assessing predictive relevance of the model says that value should be larger than zero (0) to suggest predictive accuracy of the model. As a rule of thumb, values higher than 0, 0.25, and 0.50 indicates small, medium and large predictive relevance of the PLS model (Hair et al., 2020). The result produce values of 0.16 for satisfaction and 0.34 for continuous usage intention indicating small to medium predictive relevance.

The sixth step is to check predictive power of the model using PLSpredict (Shmueli et al., 2016). Under this, among the many benchmarks, both the RMSE and MAE values are acceptable prediction benchmarks, depending on the symmetry of the prediction error distribution (Hair et al., 2020). The result reveals Qpredict value of 0.509 for the target construct continuous usage intention. If the prediction results; Qpredict value are better than the naïve value (that is above 0), researchers can then examine the other prediction statistics of the both PLS and linear models (Shmueli et al., 2019). Prediction statistics produce values CUI2; 1.923, as against 1.912 for the linear model. Similarly, CUI5; 1.913 as against 1.929 for the linear model. The trend goes to CUI4; 1.847 for PLS model against 1.856. Since the PLS model produced minority or nearly equal higher prediction error compare to linear model it can be argue that the model has a medium predictive power.

The last step Importance performance map analysis (IPMA) to examine the performance of each exogenous construct on the primary dependent variable (continuous usage intention). The result of IPMA produce the value of 58.7%, 69% and 73 % for the AI quality, preference and

satisfaction respectively. However, on the scale of 100, it can be seen that, AI quality has the lowest performance (58.7%), which suggests the room for managerial actions to improve the perceived AI quality.

Discussion and Hypothesis Testing

This study is concern with the relationship between AI quality and continuous usage intention of e-banking services. It also set to examine the mediating role of satisfaction in the relationship thereof. However, since previous indicates that some consumers preferred certain features to presents as the determinant for the acceptance and adoption of banking services (Merchman & Verleye, 2019). While others indicates lack of consensus and the consumers in various countries (Al-Fahim, 2013; Bolar, 2014; Ezzi, 2014). We first decides to examine whether customers preference influence the perception of AI quality, satisfaction and continuous usage intention in the Nigerian banking sector. Therefore, the first three hypotheses (H1, H2 and H3), were on the relationship between preference to perceived AI quality, preference to satisfaction and lastly preference to continuous usage intention. The bootstrapping result produced lack of support for H1, H2, and H3 ($b = 0.042$, $t = 0.611$, $p > 0.05$, $b = 0.002$, $t = 0.061$, $p > 0.05$, $b = 0.042$, $t = 0.611$, $p > 0.05$) respectively. On the other hand, H4, H5 and H6, were on the relationship between AI quality to satisfaction, AI quality to continuous usage intention and lastly satisfaction to continuous usage intention. The result produced beta values ($b = 0.501$, $t = 12.230$, $p < 0.001$, $b = 0.444$, $t = 10.515$, $p < 0.001$, $b = 0.414$, $t = 8.305$, $p > 0.05$) respectively. It therefore, in line with finding other scholars that examine IS quality and continuous usage intention (Hong, Lee & Suh, 2013; Li & Shang, 2019). Hence, hypotheses 4, 5, and 6 are supported. Implications of these findings are discuss below.

Implications of the Findings

The findings indicate that the AI quality have a positive effect on satisfaction and satisfaction has significant positive effect on the intention of continuing use of e-banking services. However, consumer preference was not significantly related to continuous usage intention of e-banking services. This is practically possible, because we observe that majority of the respondents does not have specific preference of using or interacting with e-banking services powered by AI as against those control by human interactions. The implication of this findings is that is the used of AI based services in the Nigerian context is still at it infancy level, and therefore there is still much to learn from the experience of both planners, implementers and beneficiaries. However, as Nigeria recently launched digital economic policy (Federal Ministry of communication and digital economy, 2019) we expect this relationship to change over time. This is in line with research finding that on the artificial intelligence base services, Malaysian banks customers are willing to support data sharing in an open banking system but only if their privacy and security concerns are fully addressed (“Malaysian bank customers ready to embrace AI and automation”2018). The findings of this study is therefore provides valuable insights to both the practicing managers and academics in dealing with artificial intelligence quality, preference,

satisfaction and continuous usage intention of e-banking services by discussing the overview of these concepts, and the relationships between them.

On the theoretical lens, the finding suggests that continuous-use intention, as one of the most post-adoption behaviors, is a necessary and critical indicator of customer loyalty to particular service provider. Therefore, continuous usage intention should be seen as the key to the IS success (DeLone & McLean, 1992; Davis, 1996; DeLone & McLean, 2003). This study is perhaps, the first of its kind to examine the relationships of AI chatbot quality on customer satisfaction and continuous usage intention of e-banking services. However, this research does not end without limitations such as the use of cross-sectional research design tom collected data from the respondents. The sample size is relatively small; we are not sure whether collecting more data from the large population could alter the relationships between the construct. It also based on African culture where the digital literature level is at the infancy level. It is possible to obtain different result if data could be collected from more advanced countries. The respondents are also limited to banking sectors. Collecting data from other sectors could possible bring new insights on the relationships between the research constructs. More so, the study does not consider the role of other contextual factors such as respondent's income level, gender and bank reputation that could either strengthen or weaken the relationships between AI quality, preference and continuous usage intention. More research is need to explore these relationships further by including other variables.

5. Conclusion and Recommendation

This study was set to examine the relationships between AI quality, Customer preference and continuous usage intention through the mediating effect of satisfaction. The finding provides evidence of the relationships between AI quality and continuous usage intention. However, consumer preference was not significantly related to continuous usage intention of e-banking services. This is practically possible, because we observe that majority of the respondents does not have specific preference of using or interacting with e-banking services powered by AI as against those control by human interactions. The implication of this findings is that is the used of AI based services in the Nigerian context is still at it infancy level, and therefore there is still much to learn from the experience of both planners, implementers and beneficiaries. However, as Nigeria recently launched digital economic policy (Federal Ministry of communication and digital economy, 2019) we expect this relationship to change over time. This is in line with research finding that on the artificial intelligence base services, Malaysian banks customers are willing to support data sharing in an open banking system but only if their privacy and security concerns are fully addressed ("Malaysian bank customers ready to embrace AI and automation"2018). The findings of this study is therefore provides valuable insights to both the practicing managers and academics in dealing with artificial intelligence quality, preference, satisfaction and continuous usage intention of e-banking services by discussing the overview of these concepts, and the relationships between them

Bank manager should therefore pat attention to AI quality improvement to satisfaction which in turn will lead to continuous usage intention. More so, the study does not consider the role of

other contextual factors such as trust on bank, the role of gender and income level on the relationships between AI quality, preference and continuous usage intention. Therefore, more research is need to explore these relationships further by including other variables that are included in this model.

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