Moderating Role of Bank Reputation on the Relationship between Artificial Intelligence (AI) Quality, Satisfaction and Continuous Usage Intention of e-Banking Services.

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Abstract

The purpose of this study is to identify the role of preference in perceived artificial intelligence (AI) quality and also to examine the moderating role of bank reputation on the relationship between AI quality, satisfaction and continuous usage intention of e-banking services. To test the hypotheses of the underlying research model, the study used cross-sectional research design to collect data from the respondent. Population of the study consists of all banks' customers that used e-banking services within the Nigerian banking sector. 306 responses from the bank customers were useful for analysis. Data were analysed using PLS-SEM approach with aid of statistical software smartPLS 3.2.8. The result suggests that there is positive and significant relationship between AI quality, satisfaction and continuous usage intention of e-banking services. However, mediation relationship is moderated by the perceived bank reputation in terms of perceived trust. Customer orientation as the second dimension of bank reputation does not moderate the relationship between AI quality, satisfaction and continuous usage. This finding is therefore in line with suggestions that customer value from analytics and AI technologies begins on reputation. While this study recommends managers to support data driven

culture through innovative analytical capability by the AI system. It also provide new insights by indicating that building a strong, foundation of trust in transparency on how customer's data is collected shared, used and protected could boost the relationships. As regard to managerial and theoretical implications, this study contributes to the emerging discussion on the dynamics nature of the relationships between artificial intelligence service quality, satisfaction and continuous usage intention. It does so by jointly analyzing the effect of bank reputation on the relationship between preference, AI quality, satisfaction and continuous usage intention of e-banking services.

Keywords: Artificial Intelligence, Bank reputation, Quality, Satisfaction, Continuous Usage Intention.

Introduction

Artificial Intelligent (AI) implementation is consider among the most radical innovation an organisation could ever made in the context of service offering. It is therefore important for the firm to critically analyse the effect of AI implementation not just for their own success but also for the customer's acceptance, quality, satisfaction and continuous usage [1]. However, empirical evidence suggested that the interval between AI implementation and acceptance and willingness to used AI systems has found to be longer in anticipated [2]. For instance, whereas some firm were forced to scale down AI investment due to poor services experienced and outright rejections from their customers [3-5]. [6] has found it took virtual agent or chatbots powered by AI almost two decades before they were recognised as potential source of value creation and adopted in the financial service delivery. These systems were considered to be too ambitious, unrealistic, hard to used and ineffective .

On the other hand, previous studies indicate that chatbots or virtual agents has some advantages over human service agents in the sense that they virtually and semoulteneously process unlimited number of transactions with minimal costs and penalties [7, 8]. Therefore, considering the fact of chatbots are designed to have virtual presence and commonly linked to online transactions [7, 9] it is not surprise that virtual agents are now deploy in different service setting ranging from hotel booking to flight reservation, tourism recommendations [10], medical services [11] and recently in e-banking transactions [12].

In doing so, when bank used a large sum of capital to develop or rather implement AI system to offer digitalise banking services to the customers and alike, the expectation was that such AI investment would lead to customer satisfaction and continuous usage [13]. But this assumption could be dangerous when the AI system failed to deliver a desire result. More so, developing countries has their own peculiarities; what works in Silicon Valley may not work perfectly in Nigeria. From the strategic information system (IS) research, the most important aspect of IS success is that of system usage [14]. On the other hand, establishing a direct linkage between IS quality, satisfaction and continuous usage has not been easy for many organisations. This is particularly relevant to the Nigerian banking sector characterises as been dynamic due to technological disruptions, customer sophistication and changing regulations that resulted in the shrinking market share and reduction in profitability [1, 8, 15, 16]. This necessity the need to conduct another study.

Some studies suggested that customers stay loyal because they are satisfied and want to continue their relationship with a firm [17]. And satisfaction affects future consumer

choices, which in turn leads to improved continuous usage intention. But in digital banking even the most satisfied customer is vulnerable to situational factors such as perceived, ease of used, and price [18]. We built on this to argue that in the banking sector, satisfaction alone is not likely to be the sole predictor of continuous usage intention of e-banking services.

A number of studies has shown that the relationship between customer satisfaction and continuous usage (repurchase) intention can be weak. More so, [19] established that, inconsistency in studies suggest the necessity for introducing a moderator to checkmate if the relationship can vary at different level of moderation. In this study we propose bank reputation in terms of customer orientation and trust to moderate the relationships between satisfaction and continuous usage of e-banking services powered by AI. Accordingly perceived trust significantly influence the way an individual customer thinks and behave in an online platform. The link between satisfactions, trust have been examine in the context of marketing and consumer behaviour [20-22], with little consideration to continuous usage intention [2, 4, 5].

Consequently, trust as moderating variable in the relationships between satisfaction of AI service quality and CUI is yet to be investigated. Therefore such consideration could increase our theoretical understanding of how perceived trust influences the relationship between AI quality, satisfaction and continuous usage Intention of e-banking services. The rest of the paper was organised as follows. Section two 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 present the results, implications, limitations and conclusions of the study.

Theoretical Framework and Hypotheses Development

AI chatbot is a form of robot combined with artificial intelligence, machine learning and natural language processing that gathers information about its environment by input from sensors and, based on this input, changes its behavior. In a more theoretical lens AI chatbot is defined as “conversational agents exploit natural language technologies to engage users in text-based information-seeking and task-oriented dialogs for a broad range of applications” [23]. As AI powered chatbot was meant to mimic human personality and intelligence by creating interactive and delightful discussions with users [12]. Consequently, an intelligence chatbot should have the ability to understand user intent and autonomously achieve the goal of the conversation [18, 24, 25]. This type of chatbots are considered to be the better version of the rule-based chatbots. AI powered chatbot thus covers a wide range of disciplines such as machine learning, natural language processing and deep learning capability. Despite all these, there insinuation among the industry leaders and researchers that chatbots have failed to deliver a seamlessly, delightful user experiences in the virtual environment [15, 26, 27] 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 back end office operations. This brings the issue of issue of perceived service quality and continuous usage of AI system.

From marketing literature downward to organisational studies service quality has been difficult to define due individual differences among customers. As [28] pointed out that a particular service has quality if customers’ enjoyment of it, exceeds their perceived value of the money paid. Yet, many scholars questioned the concept of customer enjoyment [29]According to [29] service quality is an evaluation of the performance, made by the customer, which is based on different specific features attached to the service. This difficulty become apparent when it comes to AI quality in the digital ecosystems.

Therefore, the issue of service quality and its impact on satisfaction and their effect has caught the attention of researchers because of its potential to influence subsequent behavioural intention and overall competitiveness of a firm [30]. For instance, [31]indicates that as the service quality increases the possibility of customer satisfaction also increased. [32] also document that perceived service quality has a direct effect on customers' satisfaction their willingness to patronize that service provider in subsequent usage intention. Although the extent of literature information system (IS) and service marketing suggests AI system quality, satisfaction and continuous usage intention could be connected together [14]. But empirical evidences reveals that this relationships does not seems to be linear in all context [33]. In the banking sector, scholars have struggled to understand the relationship between the satisfaction construct and its antecedents and consequences [34]. More so, establishing a direct linkage between IS quality, satisfaction and reused intention has not been easy for many organisations [35]. Therefore, as the relationships among the AI system quality, satisfaction and continuous usage intention has been ambiguous, leaving the extent and direction of causality unresolved [32, 36, 37] the following hypotheses are developed.

H1 AI quality has significant effect on continuous usage intention of e-banking services empowered by AI.

H2 AI quality has significant effect on customer satisfaction of e-banking services empowered by AI.

H3. Satisfaction mediate the relationship between AI quality and Continuous usage intention of e-banking services empowered by AI.

H4. There is significant relationship between preference and perceived AI system quality among bank customers.

H5. There is significant relationship between preference continuous usage intentions of e-banking services empowered by AI

Bank Reputation as Moderating Variable

In the banking sector, reputation plays a vital role in service markets. For instance, a lack of physical evidence to evaluate service quality in the virtual system makes customers' decision process complicated. Therefore, in the context of digital banking customers are likely to benefit from bank reputation due increase of service intangibility which also increase uncertain and perceived risks. In other words, "in the context of services containing high risks, customers are more likely to consider the firm's reputation to decrease uncertainties of its services [38, 39]. Hence, it is rationale to argue that the bank reputation will have important role in helping to reduce risks and uncertainties which are perceived by the customers in choosing service provider in the banking sector. Accordingly, bank reputation can be conceptualized to have direct and indirect interaction effects [40]. It is also be measured as a single dimensional measurements with many items [22, 32, 36] however, some scholars indicates the inadequacy of such approach [21, 41]. In other word, bank reputation is a stakeholder-specific phenomenon which is far from being a single dimensional construct different stakeholders may have different assessment of reputation [39]. In this study, bank reputation is conceptualise to include two independent dimension of trust and customer orientation. These dimensions are discussed below.

Customer orientation is defined as "the degree to which the service worker practices the marketing concept by trying to help the customers make purchase decisions that will satisfy customer needs". In the banking sector, this orientation refers to set of beliefs that puts customers' interest first [42] by focusing on their needs, values and beliefs on continuous basis. It is a behaviours necessary for creation of superior value for the

customers [11]. That is a customer oriented firm will likely to engage in behaviors directed at value creation and relationship development with customers [43]. Customer orientation was found to be a strong predictor of service success or failure to satisfied expectation and is highly correlated to repurchase intentions (Guenzi, Luca & Troilo, 2011; Frambach, Fiss & Ingenbleek, 2016). Thus it is possible to understand how customer orientation affect other marketing such as satisfaction and continuous usage intention [44]. It is therefore appropriate to propose that customer orientation could serve as both predictor and a potential moderator in the relationship between customer satisfaction and continuous usage intention of e-banking services. The following hypothesis is thus developed.

H6. Customer orientation as dimension of bank reputation is significantly related to continuous usage intention of e-banking services empowered by the artificial intelligence system.

H7. Customer orientation as dimension of bank reputation moderates the relationship between artificial intelligence quality, satisfaction and continuous usage intention of e-banking services empowered by the artificial intelligence system.

Although, satisfaction and trust have been widely explored by researchers for their effects on repurchase intention in the context of online consumer behavior [32]. But few studies have actually examined the relationships between trusts, satisfaction, repurchase intention [4, 29, 45]. [45] developed a model to explore the relationships between satisfactions, trust and repurchase intention and discovered that satisfaction influence usage intention and trust mediate the relationship. But even those studies did not considered the role of AI quality in such relationship. In addition, both the effect of both satisfaction and trust vary in different contexts [45]. Therefore as the impact of trust on continuous usage intention is not independent from its context [6], several scholars have called for further studies to examines the effect of trust on the relationship between satisfaction and continuous usage intention [6, 46]. More so, there still exist an emerging call for understanding the organisational context under which customer trust influence satisfaction and continuous usage intention [6]. More recently some studies indicates the possible interaction of trust between satisfaction and continuous usage intention as either mediator or moderating variable [45]. It therefore, appropriate to examine the direct and moderating effect of trust on the relationship between AI quality satisfaction and continuous usage intention.

H8. *Perceived trust as dimension of bank reputation is significantly related to continuous usage intention of e-banking services empowered by the artificial intelligence system*

H9. Perceived trust as dimension of bank reputation moderates the relationship between artificial intelligence quality, satisfaction and continuous usage intention of e-banking services empowered by the artificial intelligence system.

Methodology

To test the hypotheses of the study in the underlying research model, the study used variance-based structural equation modelling; the partial least squares (PLS-SEM) approach, which is widely used in social science and information systems research [47]. PLS-SEM is useful for success factor research (Albers, 2010) to explain and predict the key target variable of interest [48]. Population of the respondents consists of all banks' customers that used e-banking services within the Nigerian banking sector. As the exact number of these people is not known by the researchers, the study used snowball sampling non-probability sampling procedure was used for the data collection. In total, 353 responses were received over a three-month two weeks period. After, first cross-checking of retrieved questionnaire 27 suspicious samples which straight lining such as

4.4.4.4 or 5.5.5.5 all through were excluded. Further investigation of the data, 19 more additional responses were identified and eliminated leaving a total of 306. As regard to instrument of the study, AI quality was measured using 9 items [29] Preference was measured using 5 items [29]. Likewise, satisfaction, continuous usage intention were measured 5 and 4 items respectively [29, 31, 49, 50]. Similarly, 10 items used to measured bank reputation in terms of customer orientation and trust of each construct. The scale was adopted from the previous studies and it allows measuring "individual dimensions of corporate reputation from the view of the customer and to understand how these individual dimensions work individually". Data were analysed using PLS-SEM approach with the aid of SmartPLS statistical software 3.2.8 [51].

Procedural approach was used to minimise the occurrence of common method bias in the study. Firstly, the data were collected from the single source which are the bank customers in Nigeria. Secondly, a clear instruction on how to complete the survey was provided in the questionnaire. Thirdly, respondent were informed that there is no right or wrong answers the researcher is only interested in knowing their honest opinion [52]. Fourthly the anonymity and confidentiality of the research participants were ensured [16]. Lastly, the questionnaire statement were pretested to avoid confusion and unnecessary difficulties in answering the questions [53]. Therefore, it is safe to assume that common method bias was of little concern in the current study.

Result and Discussion

This study conducted a variance-based SEM analysis by means of PLS using the SmartPLS 3.2.8 software [8, 18, 53]. Figure 2 and Tables 1 and 2 show the results of the research model. The results assessment considers two stages: First, the study assessed the measurement model and then the structural model [21, 24, 54]. This study used reflective measurement model for all the research construct consists of preference, AI quality, satisfaction, continuous usage intention and bank reputation (i.e. trust and customer orientation).

The first step in assessing measurement model starts with evaluation of individual item reliability through indicator loadings. The rule of thumb says that an indicators loadings above 0.7 is indicates good reliability but in an exploratory research like the current study an indicators loadings of 0.6 is accepted to established item reliability [55]. The study assessed the quality of the reflective measurement models by checking the standardized outer loadings of the items in the research model starting from AI quality, continuous usage intention, customer orientation, customer, satisfaction, preference and trust. From the Table 1, it can be seen that indicators loadings for the items in the research model are within the accepted benchmark of 0.6 and above for the exploratory study. Thus, provides acceptable item reliability [12].

Table 1

Cross loadings

Item	AI Quality	Cus Orie	CUI	Cus Satls	Pref	Trust
QUA2	0.781					
QUA3	0.691					
QUA4	0.622					
QUA5	0.762					
QUA6	0.810					
QUA7	0.705					
QUA8	0.755					
CO1		0.735				
CO2		0.805				
CO3		0.842				
CO4		0.793				
CO5		0.719				
CUI1			0.701			
CUI2			0.829			
CUI3			0.835			
CUI4			0.831			
CUI5			0.735			
CUS1				0.751		
CUS2				0.650		
CUS3				0.918		
CUS4				0.915		
CUS5				0.835		
PRP1					0.687	
PRP2					0.797	
PRP3					0.714	
PRP4					0.629	
Trt1						0.807
Trt2						0.862
Trt3						0.782
Trt4						0.654

The second of step of establishing quality criteria for the measurement model is that of internal consistency reliability using composite reliability [56] and the rule of term says that higher value indicates high level of reliability [57]. However, a reliability values of 0.6

to 0.7 are considered acceptable for exploratory research and 0.7 and 0.9 indicates satisfactory good reliability [47]. However, CR value of 0.95 are problematic as such indicates redundancy thereby reducing construct reliability [42, 58]. It may also indicate undesirable response such as straight lining from the respondents [55]. Also, Cronbach alpha is less precise measure of internal consistency reliability since the items are unweighted compare to CR which the items are weighted. Nevertheless the true construct reliability is within the two extreme values of 0.5 for Cronbach alpha to 0.7 of CR. From the Table 2 the result shows that construct reliability through both CR and Cronbach alpha has been established.

Table 2

Indicator reliability and validity

Construct	Cronbach's Alpha	rho_A	Composite Reliability	AVE
AI Quality	0.856	0.856	0.891	0.540
ContUsed Intention	0.847	0.858	0.891	0.622
Cus Orient	0.839	0.843	0.886	0.608
Preferance	0.729	0.843	0.801	0.503
Satisfaction	0.875	0.900	0.910	0.673
Trust	0.781	0.794	0.860	0.608

The third step in the assessment of the measurement model is convergent validity (CV) diagnosis. Convergent validity is the extent to which the construct converges in order to explain the variance of its items [59]. Therefore, the criterion for measuring CV is the average variance extracted (AVE) for all the items for each construct [47, 55, 60]. It is inevitable that the latent construct needs to explain a minimum half of the variance in the indicators [61]. Under this, the minimum accepted AVE is 0.5 or higher. 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. As can be seen in Table 2 all the construct AVE is within the benchmark of 0.5 and above.

The fourth step is to assess discriminant validity, which is the extent to which a construct is empirically distinct from other constructs in the structural model. Traditionally, discriminant validity has been assessed using [62]'s criterion where each construct's AVE should be compared the squared inter-construct correlation of that same construct to see that if the shared variance for all model constructs is not larger than their AVEs [50, 57]. However, since [51] has shown that the Fornell-Larcker criterion does not perform well in assessing discriminant validity, particularly when the indicator loadings on a research construct differ only slightly (when all the indicator loadings are between 0.65 and 0.85). The heterotrait-monotrait ratio (HTMT) of the correlations was considered [51]. The result of analysis (Table3) returned a HTMT value ranging from 0.472 to 0.091 for all the constructs. In line with this, discriminant validity for all the construct was established [51]

Table 4

Discriminant Validity HTMT

Construct	AI Qual	CUI	Cus Orient	Preference	Sat*Orient	Sat*Trust	Sat	Trust
AI Quality								
CUI	0.472							
Cus Orient	0.294	0.547						
Preference	0.119	0.225	0.091					
Satisf*Orient	0.208	0.445	0.715	0.062				
Satisf*Trust	0.219	0.358	0.591	0.061	0.695			
Satisfaction	0.503	0.574	0.443	0.159	0.344	0.414		
Trust	0.298	0.888	0.658	0.087	0.524	0.533	0.509	

The fifth step is to assess the structural model estimates in order to examine the hypothesized relationships among the research constructs in the conceptual model [55]. The first 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 indicate collinearity [63]. The result for collinearity diagnosis shows that collinearity is not an issue as the VIF values for all the construct ranged from 1.104 to 1.824 respectively. Next, the size and significance of path coefficients are used to test the hypothesised relationships in the structural model figure one. The path coefficients are standardized values that may range from +1 to −1 and the closer the path coefficient values are to 0 the weaker they are in predicting the endogenous constructs known as dependent variables [63]. Likewise, the closer the path coefficients values are to the 1 the stronger they are in predicting the endogenous constructs [63]. The result of the size and significance of path coefficients is presented in the Table 5.

Table 5

Size and Significant of the Coefficients

Hypotheses	Beta	R^2	STD	T Statistics	P Values	2.5%	97.5%	Support (Hypotheses)
AI Quality -> CUI	0.134		0.046	2.903	0.004	0.047	0.222	Yes
AI Quality -> Sat	0.404	18	0.056	7.205	0.000	0.305	0.517	Yes
Cus Orient -> CUI	0.055		0.053	1.039	0.299	-0.052	0.161	No
Pref -> AI Quality	0.086		0.054	1.600	0.110	-0.026	0.195	No
Preference -> CUI	0.110		0.035	3.118	0.002	0.049	0.184	Yes
Preference -> Sat	0.100		0.060	1.680	0.094	-0.017	0.216	No
Satisf*Ori -> CUI	-0.094		0.065	1.448	0.148	-0.200	0.056	No
Satisf*Trust -> CUI	0.139		0.068	2.054	0.041	-0.028	0.256	Yes
Satisfaction -> CUI	0.148	65	0.058	2.539	0.011	0.037	0.257	Yes
Trust -> CUI	0.640		0.069	9.306	0.000	0.502	0.770	Yes

[64] introduced the use of confidence intervals (both lower and upper bound) with PLS-SEM. According to [64] a confidence intervals can be used in a similar to p-value and t-statistics and the intervals excluding zero are statistically significant. [65] also suggested that with the used of confidence intervals the used of "dichotomous approach" of significance testing is avoided as authors will be able to consider other methods to detect practically significant relationships. The result of confidence interval with lower and upper bound is presented in Table 4.

Next 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 [66]. The R^2 value ranged from 0 to 1 with higher value indicating a greater explanatory power. 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 [51]. However, in an exploratory research such as the current study an R^2 value of 0.10 and above can be acceptable. In other words, the acceptable value of R^2 are based on the context to which the research is conducted. In some disciplines an R^2 of 0.10 is seen as satisfactory [55].

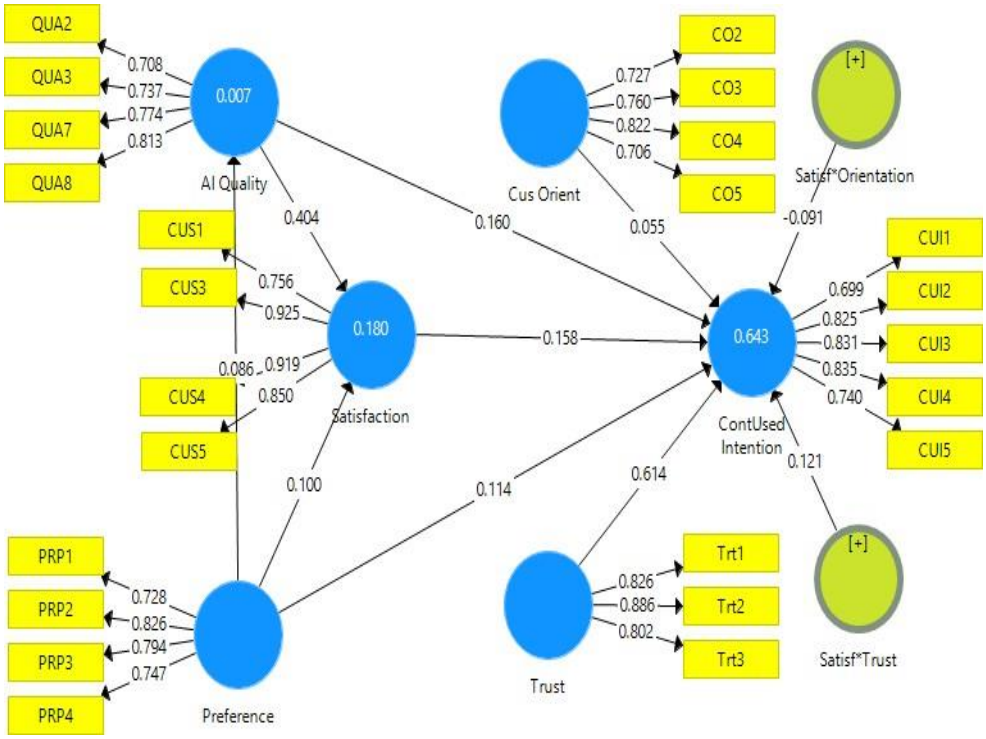

Figure 1. *Coefficient Determination*

The structural model estimation provides the path coefficients and R^2 values shown in figure 1. In order to assess the results, the study used the bootstrapping method to test the strength and significance of the hypothesized path coefficients. The bootstrapping method in SmartPLS was run using 5,000 subsamples. While the relationship between AI quality and satisfaction produced a moderate R^2 of 18% as expected path coefficients in the analyzed moderated mediation model explain approximately 64% of the variance linked to the key target construct continuous usage intention of e-banking services (R^2 = 0.64). Out of these, six hypotheses were supported and four hypotheses not supported, as shown in Table 4.

In addition to assessing the R^2, the study also checked the effect size (f^2) to establish how R^2 values will changed if a construct is omitted from the model, using a threshold of 0.02, 0.15, and 0.35 for a small, medium and large effect respectively [55]. First, the result indicate that the effect of removing AI quality on CUI is very small (f^2; 0.06), but moderate on satisfaction (f^2; 0.20). This indicate that substantial effect of AI quality on CUI passed through satisfaction. The second, effect of omitting the perceived trust on CUI is large (f^2; 0.62) which confirm our initial assertion that the relationship between satisfaction and CUI is moderated by perceived trust. For rest of the antecedents constructs a small effect was found for preference on continuous usage intention (f^2 0.03), preference on satisfaction (f^2 0.07) but zero effect on perceived AI quality (f^2 0.00). Contrary to our expectation, preference was found to have zero effect size on perceived AI quality. Lastly, customer orientation as the second dimension of bank reputation has zero effect on CUI.

Similarly, as regards to overall model fitness, this study employed the Standardized Root Mean square Residual (SRMR), which was used to measures model fitness [51] Under this a value of zero indicates perfect fit, and A value less than 0.10 or of 0.08 is generally considered acceptable as a good fit [36]. The result of analysis returned an SRMR value of 0.085 which is also within the accepted threshold value of .08 indicating a very good fit as seen in Table 5.

Table 6

Model Fit

	Saturated Model	Estimated Model
SRMR	0.083	0.130
d_ULS	3.216	7.870
d_G	1.578	1.695
Chi-Square	2430.687	2488.771
NFI	0.600	0.590

The seventh step is to apply the PLS-predict of [66], a procedure used to assess the quality of out-of-sample predictions of models for the key target constructs (Continuous usage intention). Under this, once the Qpredict values are above zero, the prediction error of a PLS-SEM analysis can be assess. As can be seen in Table 7 all indicators have Qpredict values above zero. The RMSE values are compared to a naïve value obtained by a linear regression model (LM) that generates predictions for the measured variable [63] and the values should be smaller. Out of the five indicators for measuring continuous usage intention the PLS-SEM results of four indicators for performance have smaller prediction errors than the linear model benchmarks. The study thus to conclude that the model has medium to high predictive power [9, 25, 63, 66], as seen in Table 7.

Table 7

PLSpredict result

CU Intention	Q^2_predict	PLS Model		Linear Model	
		RMSE	MAE	RMSE	MAE
CUI1	0.182	**1.608**	1.161	1.743	1.366
CUI2	0.320	**1.101**	0.658	1.585	1.320
CUI3	0.211	**1.201**	0.726	1.649	1.298
CUI4	0.163	1.900	1.542	**1.865**	1.568
CUI5	0.206	**1.830**	1.436	1.835	1.531

When comparing the PLS-SEM results against the linear model benchmark, the numbers in bold indicate where the prediction error is smaller. MAE mean absolute error, RMSE root mean square error.

From Table 7 above it can be argue that the proposed model has a medium to high predictive power [66] as out of the five items for measuring continuous usage intention has smaller prediction error.

The eight step is to perform the importance performance map analysis (IPMA) for the key target construct which continuous usage intention of e-banking services. The goal is to identify antecedents construct that have high importance for the target construct (continuous usage intention), but indicate a relatively low performance on the construct. The result is seen in Table 8.

Table 8

The Importance Performance Analysis (IMPA)

Construct	Performance	Importance
AI Quality	58.723	0.158
Cust. Orient	78.317	0.020
Preference	71.805	0.119
Satisfaction	72.736	0.107
Trust	72.206	0.660

From the Table 8 the result of IPMA indicates that Attitude has a high performance 72.886 but low importance was attached to it by the respondents (0.020) it is therefore necessary for Nigerian banks to improve their reputation in terms of being a customer friendly in both cost and prices. Similarly, the result indicates that trust has both importance (66%) and relatively high performance on the target construct (72%). Nevertheless, there is still room for improvement to ensure sustainability. More importantly, the result reveals that AI quality has the lowest performance (58%) in predicting the target construct continuous usage intention. It is therefore necessary for bank managers to improve the performance of AI quality among the other organisational resources for digital banking. Future studies can look for more ways to improve the performance of these constructs.

The last step in the assessment of structural model is to conduct robustness checks on the analyses to see if the results differ when analysis decisions are altered [63]. Typically, this include things such as adding or removing variables, mediation, moderation, as well as modeling nonlinear relationships etc. [48, 67]. In this study, trust and customer satisfaction as dimension of bank reputation were removed and this resulted in the reduction in the R^2 value for CUI (0.31), as seen in figure 2. This result, justified our decision to include bank reputation as a moderator in the relationships between preference, AI quality, satisfaction and continuous usage intention. Implications for this finding could therefore be discuss as follows.

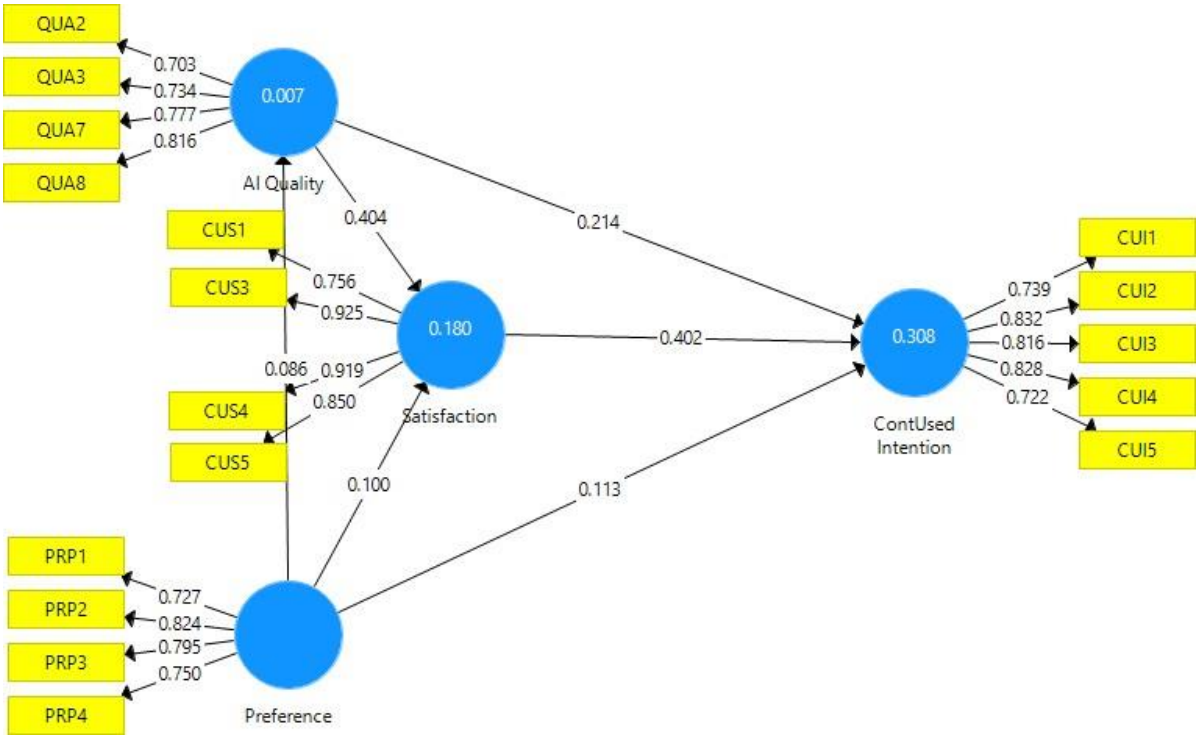

Figure 2. *Robustness check to see if result differ when decision is alter (Hair et al., 2020)*

Discussion of Findings

This study set to examine the causal relationship between preference and perceived AI system quality and AI quality to satisfaction and continuous usage intention. Further, it investigated the moderating role of trust between AI quality, satisfaction and continuous usage intention. The findings of this study suggested that preference is a strong predictor of perceived AI quality, and AI quality predict satisfaction and satisfaction mediate relationship between preference, quality and continuous usage intention among bank customers in Nigeria. More so, trust as first dimension of bank reputation moderates the relationships. However, customer orientation as the second dimension of bank reputation does not moderate the relationship thereof. This findings is in line with finding of [9]. But differed with the finding of [7]which examines the effect of customer orientation on service performance and outcome behaviors. Hence, the study provides new insights on the dynamics nature of the relationships between artificial intelligence base services quality, satisfaction and continuous usage intention. It does so by jointly analyzing the effect of Bank reputation on the relationship between preference, AI quality, satisfaction and continuous usage intention of e-banking services. More so, it is the first study to introduce the moderating role of bank reputation in the relationship between these construct.

As regard to whether we applied the right statistical approach to assess the measurement model and test the underlying hypotheses we argued that both CB-SEM and PLS-SEM emerged at the same time [68] but PLS-SEM was used because it offer a structural equation modeling approach with much greater flexibility compared to CB-SEM [55, 57, 63] also indicates that PLS-SEM is more useful in the earlier phases of theory development which is one of the basis of conducting this study. Thirdly, PLS-SEM

provides more accurate estimates with small sample sizes [59]. Fourthly, PLS-SEM is more appropriate when models are complex and therefore more likely to result in model convergence when studying a large number of observed and/or latent variables [47, 55, 57, 63, 69]. Fifthly, PLS-SEM was chosen against CB-SEM as prediction is among the key objective of the current study [66]. Lastly, the use of PLS-SEM allowed the researchers to executes some advance analysis such as the used of continuous moderators, which were not possible or at minimum difficult with CB-SEM [63]Specifically, we based our decision that, [48, 54, 67, 70]discovered that "composite-based SEM methods such as partial least squares (PLS-SEM) are the preferred and superior approach when estimating mediation and conditional process models, and that the PROCESS approach is not needed when mediation is examined with PLS-SEM.

Conclusion

The study conclude that there is significant relationship between AI quality, satisfaction and continuous usage intention of e-banking services. However, this relationship is strongly moderated by the perceived bank reputation in terms of trust. The result indicates that trust is a good moderator between AI quality, satisfaction and continuous usage intention. Commercial banks should therefore, pay more attention to reputational trust in order to improve their performance in the virtual ecosystem. This finding can be used to guide both managerial and policy actions on AI system.

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Appendices

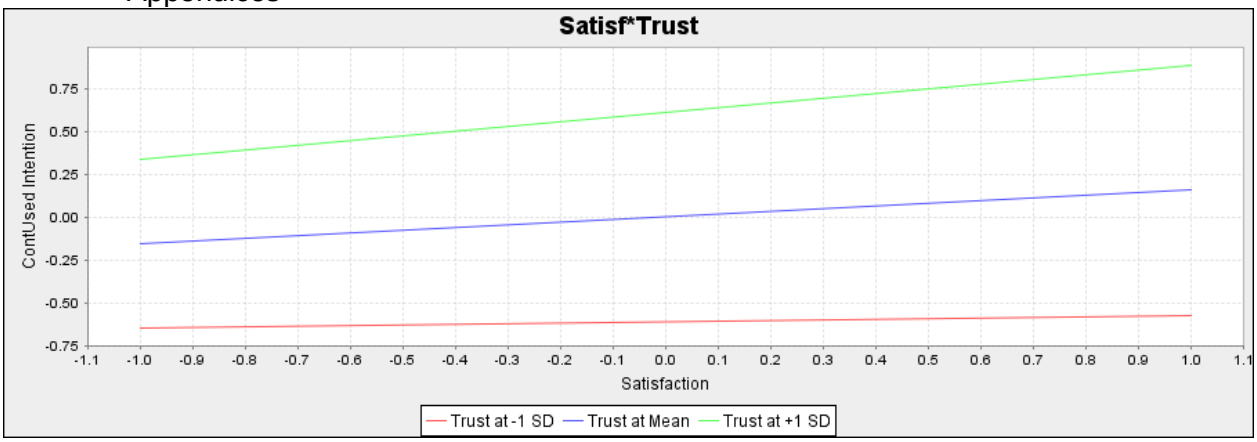
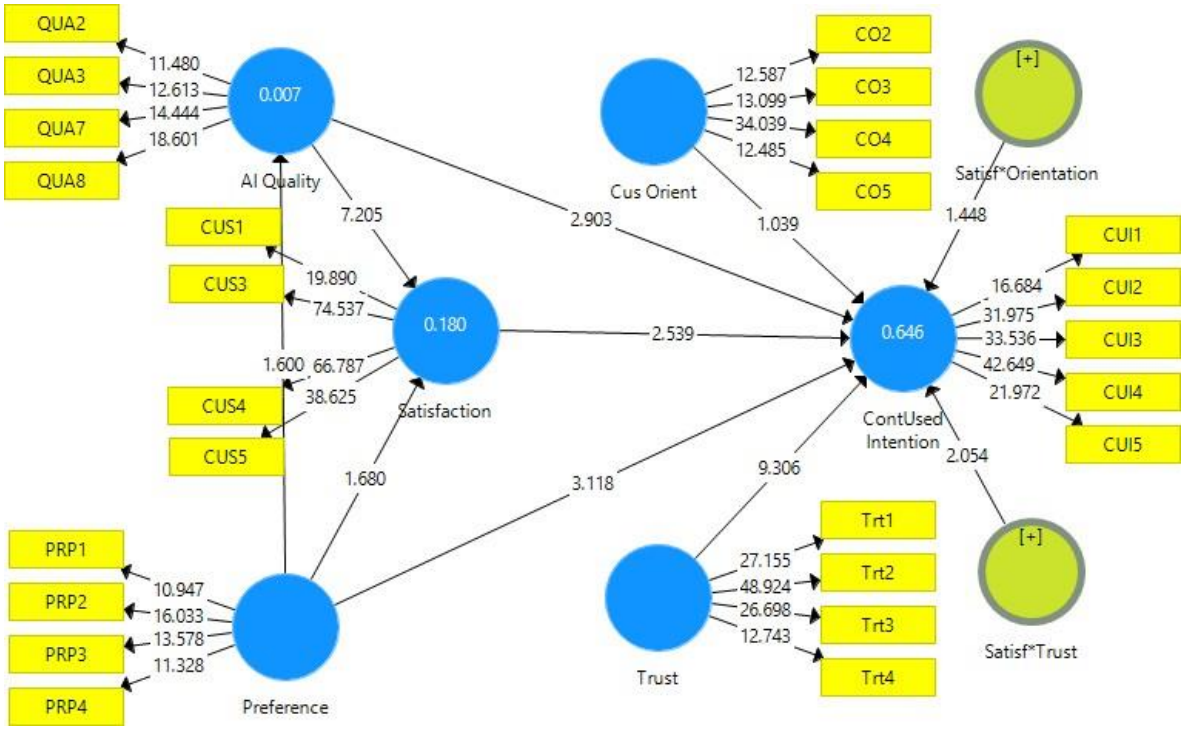


Table 3

Fornell and Lacker criteria

Construct	AI Qual	CUI	CO	Pref	Sat*Ori	Sat*Trust	Sat	Trust
AI Quality	**0.735**							
CU INT	0.419	**0.788**						
Cus Orient	0.241	0.388	**0.780**					
Pref	0.184	0.280	0.123	**0.709**				
Sat*Ori	-0.169	-0.388	-0.559	-0.093	**0.709**			
Sat*Trust	-0.205	-0.358	-0.446	-0.129	0.575	**0.684**		
Satisf	0.448	0.493	0.311	0.299	-0.253	-0.387	**0.820**	
Trust	0.317	0.749	0.436	0.168	-0.431	-0.521	0.451	**0.780**


QUA2
QUA3
QUA7
QUA8
11.480
12.613
14.444
18.601
0.007
AI Quality
7.205
2.903
CUS1
CUS3
CUS4
CUS5
19.890
74.537
1.600
66.787
38.625
0.180
Satisfaction
1.680
2.539
3.118
PRP1
PRP2
PRP3
PRP4
10.947
16.033
13.578
11.328
Preference
Cus Orient
12.587
13.099
34.039
12.485
CO2
CO3
CO4
CO5
1.039
[+]
Satisf*Orientation
1.448
0.646
ContUsed
Intention
16.684
31.975
33.536
42.649
21.972
CUI1
CUI2
CUI3
CUI4
CUI5
2.054
9.306
Trust
27.155
48.924
26.698
12.743
Trt1
Trt2
Trt3
Trt4
[+]
Satisf*Trust