ARTIFICIAL INTELLIGENCE INFLUENCE ON DIGITAL FINANCIAL INCLUSION AND EDUCATION IN SOUTHWEST NIGERIA

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Article History: Received: 22.05.2023 **Revised:** 05.06.2023 **Accepted:** 26.07.2023

Abstract

This Study examined the influence AI-enabled fraud detection and AI-enabled personalised banking automation on advancement of financial inclusion in the Southwest Region of Nigeria. While most studies have largely examined artificial intelligence independently, to the neglect of an empirical investigation on AI's impact on financial inclusion especially in the rural context of Nigeria. Survey method was employed in determining how AI-enabled fraud detection and AI-enabled personalised impact financial inclusion in Southwest Nigeria. The result of the standardized beta coefficient (-0.064; P-value>0.05) shows the probability of having T-statistic as large as 1.187 in absolute value is above 0.05 level. Further insight indicates a positive relationship between AI-enabled personalised banking automation and financial inclusion such that improvements in AI-enabled personalised banking automation will translate to a proportionate positive impact on financial inclusion.

Keywords: Artificial Intelligence; Financial Inclusion; Financial Literacy, Financial Education, Rural Dwellers.

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DOI: 10.31838/ecb/2023.12.s3.761

1. INTRODUCTION

It has been challenging for the traditional banking system to include all adults who are bankable on a global scale. According to the World Bank's Global Findex database, there is an estimate of 1.7 billion adult nonbank customers worldwide as of 2017 (Demirgüç-Kunt, Klapper, Singer, Ansar, & Hess, 2020). Consequently, neither traditional nor online financial institutions have an account for these individuals. Developing nations have the highest concentration of unbanked or underbanked people (Goh, Mah, & Chay, 2022). Also, a sizable portion of the unbanked population is composed of the impoverished (Adeleke, Iyanda, Osayomi, & Alabede, 2022). According to a survey by the British Research Firm Merchant Machine, the top 6 nations with the largest percentage of unbanked citizens are Vietnam, Philippines, Morocco, Egypt, Mexico, and Nigeria. The list frequently includes developing nations (Demirgüç-Kunt et al., 2020).

By region, 50 per cent of the total population of the Africa and the Middle East are unbanked. South and Central America, Eastern Europe and the Asia Pacific followed with 38 per cent, 33 per cent, and 24 per cent unbanked population respectively (David & Williams, 2022). Kshetri (2021), reports that aside from unbanked individuals, about 200 million small and medium enterprises (SMEs) in developing countries are financially excluded. In developing nations like Nigeria, the financial sectors are frequently characterised as dangerous, underdeveloped, urban-based, anti-poor, and unfavourable to young and women (Kuada, 2019).

The banking industry has continuously attempted to tap into the unbanked consumer segments, albeit with limited success. The assumption is that a sizable portion of the economy remains untapped, underdeveloped, and less productive (Makina, 2017). According to Bayero (2015), the unbanked population, which is primarily made up of low-income customers, is vulnerable to financial exclusion, and being financially excluded is equivalent to facing economic difficulties. Hence, financial insolation is not only a factor that supports poverty rate among the low-income earners, but also a factor that intensifies poverty's grip on people. Financial exclusion strengthens the effect of poverty in the lives of individuals. These fears directly or indirectly led to the popularity and prioritization of financial inclusion across the world.

Financial inclusion, according to the World Bank, is a state in which all people have access to financial services offered by formal institutions and may use at least one formal account to conduct financial transactions at a reasonable cost (Demirgüç-Kunt & Singer, 2017). Financial inclusion, according to the National Financial Inclusion Strategy, is attained when people in Nigeria have simple access to a wide range of financial services that satisfy their requirements at a reasonable price. (Nandan, Kumar, & Koppula, 2021). The availability and equality of opportunities for people and businesses, particularly low-income people and micro and small businesses, to access a range of suitable financial services, such as savings, credit, payment, and risk management products, are broadly defined as financial inclusion by Chen, Kumara, and Sivakumar (2021). For Klapper (2016), financial inclusion means a household's access to and ability to effectively use fitting financial services that meet their needs such as savings, transactions, payments, and credit facilities delivered responsibly and sustainably. Financial inclusion has also gained attention in the academic community, with academic submissions focusing on its potential to boost economic growth (Nkwede, 2015), foster financial prosperity among the populace (Chima, Babajide, Adegboye, Kehinde, & Fasheyitan, 2021); and reduce income inequality and poverty (Kuada, 2019; Omar & Inaba, 2020; Ozili, 2018) ; (Morgan & Pontines, 2014). Financial inclusion has benefits such as lowering poverty and fostering economic expansion. The claim is that financial inclusion increases low-income families' ability to withstand financial shocks, maintain consumption, acquire assets, and invest in elements of human wellbeing and development including health, education, and entrepreneurial ventures in their economies (Bayero, 2015).

Achieving a commendable level of financial inclusion is still a global problem, despite the importance of financial inclusion in the development of any economy (Ene, Abba, & Fatokun, 2019). For traditional banks to capture the unbanked population and drive the financial inclusion rate, there is a need to establish physical branches to offer financial services to the unbanked. The adoption of financial technology to deliver digital financial services is another cheaper alternative. Using mobile devices, computers, or the internet, digital finance provides financial services that are quicker, more effectively, and more affordably than traditional financial services (Ismael & Ali, 2021). Digital finance is the new tool for achieving financial inclusion in the modern era in which artificial intelligence (AI) remains a crucial part. Traditional banks and other financial organisations are using it in an effort to reach the unbanked population. AI, for instance, is responsible for the invention of automated teller machines (ATMs). As a result, there are far fewer cash withdrawals, deposits, and balance inquiries made in the banking hall. Customers can so use all these services without necessarily going inside the banking halls. AI has allowed banks to replace simple, repetitive tasks with more lucrative offerings like relationship banking, where financial services are personalised to the needs of specific consumers (Autor, 2015). Rafael, Jon, and Mazen (2020) posited that financial institutions have deployed AI in the areas of marketing, underwriting, and account management activities. Other benefits that financial firms have derived from AI include an increase in productivity through automation; reduction in human errors; detection of frauds and mismanagement; production of accurate and concise management information by easily detecting anomalies or trends in the sector (Chan & Nayler; Gokul, 2018).

In light of altering dynamics of competition, artificial intelligence (AI) is increasingly viewed as a catalyst for a digital shift, resulting in new operational models and consumer experiences. Many Financial Service Innovators (FSI) are making investments in innovation today and figuring out how to integrate AI, robots, and automation into their daily operations. This adoption's justifications include a need for cheaper prices, quicker manufacturing times, the provision of consistent product quality, and supply chain management (Ivanov, 2017). However, there is a growing need for a much more inclusive approach, one where the workforce is enlightened on the reasons for adopting AI and how they can also be relevant by acquiring new skill sets to remain relevant in an AI-ruled world. Indeed, financial institutions through AI are adopting AI-based anti-money-laundering, anti-fraud, compliance, credit-underwriting and smart contracts technology in their operations (Ravi, 2018).

Although, the deployment of AI has significantly improved the efficiency and productivity of the financial sector, there is still a great deal of room for process improvement, increased workplace productivity, and cost savings. Personalised customer service, fraud detection, financial advice, and improved backend procedures are just a few of the primary effects of AI now being used (Kshetri, 2021). Through the application of AI, businesses in the banking sector have been able to provide customised financial services. Financial firms can better serve clients by identifying unforeseen linkages, enigmatic patterns, market trends, and customer preferences.

In this vein**,** AI chatbots can utilise machine learning and big data to respond to client inquiriesThey can concentrate customer care on routine tasks like financial transactions and provide critical product recommendations (Noonan et al., 2022). Financial organisations can better serve their clients by mining and cleansing data such as transaction history, complaints, inquiries, and feedback to better understand customer behaviour and preferences. The use of AI by financial institutions has further improved consumer satisfaction, enhanced efficiency, and ensured customer retention in various ways, despite concerns that it will decrease customer loyalty (Maskey, 2018). For instance, Erica, a chatbot from Bank of America, offers voice and text-based financial advice to the bank's customers. Similarly, DBS Bank in Singapore utilises KAI, an AI-powered virtual assistant, to improve the client experience. KAI responds to thousands of customer enquiries and enables users to complete financial operations in real-time, whenever and wherever they choose. AI adoption also saves time and money in addition to providing a personalised offering. The use of

Erica Virtual Assistance by the Bank of America offers round the clock access to financial services; on the part of the financial institutions, it saves the cost of hiring a customer service team.

Utimately, AI makes sure that, over time, replies to frequent inquiries are already prepared, as opposed to the present situation when advisers frequently need to seek specialists for instant guidance. The ability to identify fraudulent transactions is a further advantage of AI adoption (Maskey, 2018; Noonan et al., 2022). AI technology enables computers to mimic, extend, and amplify human analysts' thought processes at a speed and scale that is unmatched by humans for fraud detection (Guanah & OBI, 2021). With AI's capacity to examine an organization's limitless number of transactions, it is better positioned to identify or detect suspected fraud, obtaining prompt, effective, and precise notifications about the possibility of a person's card or account being hacked (Hinterhuber, Vescovi, & Checchinato, 2017). In addition to these benefits for financial institutions, AI may also enhance financial inclusion.

According to Salampasis and Mention (2018), the development of digital transactional platforms that may deliver essential financial services to the world's underprivileged communities which are seen as a "goldmine" untapped market—has resulted in the formulation of a "digital financial inclusion" paradigm. Global financial inclusion has been seen to be steadily improving as a result of technological advancements, particularly the expansion of mobile devices and digital financial services. Studies on the applications of AI such as Kshetri (2021), Igwemeka, Eje, Okonkwo, Onoselogu, and Ojiakor (2020) Ozili (2021)**,** Mhlanga (2020), Makina and Walle (2019), Ene et al. (2019) have revealed the potency of using AI applications to eradicate financial exclusion and help the society to attain the elusive goal of financial inclusion in which the adult population leaving in both the rural and city dwellers, have equal opportunity to access financial products and services and thereby improve their general economic wellbeing. However, very few of these academic works focus on Nigeria. Since financial inclusion is the ultimate goal, this study intends to evaluate how artificial intelligence applications are being used in Nigeria, particularly for rural residents in the South-West area of the nation.

I. **H_0:** AI-enabled fraud detection has no significant contribution to the advancement of financial inclusion in Southwest Nigeria.
II. **H_1**: AI-enabled fraud detection has a significant contribution to the advancement of financial inclusion in Southwest Nigeria.
III. **H_0:** AI-enabled personalised banking automation has no significant contribution to the advancement of financial inclusion in Southwest Nigeria.
IV. **H_1**: AI-enabled personalised banking automation has a significant contribution to the advancement of financial inclusion in Southwest Nigeria.

2. MATERIALS AND METHODS

The quantitative method of survey was pertinent in this study to assess the impact of AI enabled customer service on financial inclusion; examine the effect of AI enabled credit and savings on financial inclusion as well as investigate the impact of AI enabled fraud detection on financial inclusion in Southwest Nigeria.

The population of this study include employees of both international and national licensed banks in Southwest, Nigeria. The Southwest states are Lagos, Oyo, Osun, Ekiti, Ondo and Ogun. The choice of Southwest states is predicated on the high presence of banks in the geopolitical zone. This has been attributed to Lagos, which is the commercial nerve centre of Nigeria (Babajide et al., 2020). In comparison to other states in the nation, the geopolitical zone is also credited with having a high spread of deposit money banks and other financial institutions, including bureau de change, microfinance bank, mortgage bank, development banks, finance house, discount house, pension managers, insurance company, and bureau de change (Babajide et al., 2020). International licensed banks include; Access Bank, First Bank, First City Monument Bank, Fidelity Bank, Guaranty Trust Bank, Union Bank, United Bank of Africa, Zenith Bank (Akamo, 2021)**.** The national licensed banks comprise of Unity Bank, Wema Bank, Eco

Bank, Heritage Bank, Citi Bank, Keystone Bank, Polaris Bank, Titan Trust Bank, Sterling Bank, Standard Chartered Bank, and Stanbic IBTC (Akamo, 2021). International licensed banks are institutions authorised by the Central Bank of Nigeria to carry out banking operations in both Nigeria as well as maintaining offshore banking operations in jurisdiction of their choice. National licensed banks on the other hand are those solitary authorised to carry out banking business operations in every state of the federation of Nigeria.

Considering the geographical makeup of the survey population, the researcher selected a total of 364 respondents, of the population area of the banks in the six states of Lagos, Ogun, Oyo, Ondo, Ekiti and Osun. The use of 364 respondents as the sample size is pegged on Israel (1992) guideline for choosing a sample size for an unknown population at a 90 percent confidence level and 10% sampling error. The attrition rate was 11% and only 324 data were analysed. Since the population for this study was large, multi-stage sampling technique was employed to reduce the population to a manageable size

3. RESULTS

Table 1: Demographic Characteristic of Respondents

Sex	**Frequency**	**Percentage (%)**
Male	164	50.7
Female	160	49.3
TOTAL	324	100.0
Age Groups	**Frequency**	**Percentage (%)**
18–- 30 Years	156	48.1
31–- 40 Years	154	47.5
41–- 50 Years	14	4.4
TOTAL	324	100.0
Marital Status	**Frequency**	**Percentage (%)**
Single	151	46.6
Married	171	52.8
Separated	1	0.3
Missing	1	0.3
TOTAL	324	100.0
Years of Experience	**Frequency**	**Percentage (%)**
1 – 5 Years	261	80.6
6 – 10 Years	59	18.2
11 – 15 Years	4	1.2
TOTAL	324	100.0

According to Table 1, 143 female workers of the selected banks participated in the study, making up 49.3 percent of the sample size, compared to 164 male employees who made up 50.7 percent of the study's sample size. A total of 156 respondents, or 48.1 percent of the sample size, are between the ages of 18 and 30. 171 respondents, or 52.8 percent of the sample total, are married, according to the subsequent results. The table reveals that 261 respondents, who account for 80.6% of the research sample size, have worked for their organizations for between a year and five years.

AI-Enabled Fraud Detection

Artificial intelligent enabled fraud detection is the fourth construct used to measure AI in this study. The items measured here are AIEFD_1 measuring the ability of AI to notify customers of any unauthorized access to their accounts. AIEFD_2 is used to ascertain the proficiency of AI to notify customers of any attempt to access their accounts from a different location and different device. AIEFD_3 measures the AI ability to alert bank customers when their passwords are compromised. AIEFD_4 focuses on AI blockage of any account that is compromised. AIEFD_5 measured the generation of security of codes and sending to customers' phone before accessing their accounts. AIEFD_6 measured the potency of the AI in identification of any fraudulent email disguised as bank-generated emails. AIEFD_7 deals with the potentiality of AI to track the origin of cyber-attacks on customers' account. AIEFD_8 measured the potency of AI in reminding customers of the need to renew and update their passwords. AIEFD_9 measured the AI in enhancing facial and voice recognition for individual customers' account. AIEFD_10 captured Alerting the bank of the use of any illicit hacking tool within the bank vicinity.

Table 2: Factor Analysis of AI-Enabled Fraud Detection

Factor Analysis of AI-Enabled Fraud Detection					
	Rotated Component Matrix				**Communalities**
	1	2	3	Initial	Extraction
AIEFD_1	.821	-.094	.005	1.000	.683
AIEFD_2	.862	-.067	.128	1.000	.764
AIEFD_3	.877	-.009	.128	1.000	.785
AIEFD_4	.223	-.024	.803	1.000	.696
AIEFD_5	-.335	-.129	.717	1.000	.643
AIEFD_6	-.672	-.195	-.048	1.000	.492
AIEFD_7	-.408	-.024	-.636	1.000	.571
AIEFD_8	-.103	.483	-.601	1.000	.604
AIEFD_9	.022	.932	-.124	1.000	.886
AIEFD_10	.028	.920	-.042	1.000	.849
Initial Eigen values (Cum%)	32.269	56.195	69.739	10.000	6.973
Measure of Sampling Adequacy					
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.					0.710
				Approx. Chi-Square	1527.440
Bartlett's Test of Sphericity				df	45
				Sig.	.000
Extraction Method: Principal Component Analysis Rotation Method: Varimax with Kaiser Normalization					
a. Rotation converged in 5 iterations					

Source; Researcher's estimate with SEM, 2022

The result of the KMO (0.710; X^2 =1527.44) and Bartlett's test (df=45; p-value<0.01) shows that 71 percent of the variations in AIEFD is explained by its underlying factors, hence the imperative for factor analysis. The test of sphericity indicates that the variables were uncorrelated implying an identity matrix. The initial communalities show the variables variances are well explained by all the components while the extraction part identified AIEFD_9(0.886) with the highest variance. At this level of loading, it is observed that with the exception of AIEFD_1(0.683), AIEFD_4(0.696), AIEFD_5(0.643), AIEFD_6(0.492), AIEFD_7(0.571) and AIEFD_8(0.604), other components met the 70 percent minimum criteria for loading factor. The rotated component confirmed three components that best explained the highest variance in AI enabled fraud detection construction. From the result in Table 4.13, it is observed that component_1 is mostly correlated with AIEFD_3(0.877), component_2 is strongly correlated with AIEFD_9(0.932) while the last component is highly correlated with AIEFD_4(0.803). These three components explained greater proportion of the (69.789%) of the total variance explained in AIEFD construct. Thus, there are good representative of the AI enabled fraud detection.

Table 3: AI-Enabled Fraud Detection and Financial Inclusion Coefficients

AI-Enabled Fraud Detection and Financial Inclusion Coefficients						
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	-8.659E-005	.054		-.002	.999
	FAC1_5	-.064	.054	-.064	-1.187	.236
	F-statistic (1.409; P-value =0.236)					
	Durbin Watson =1.90					
a. Dependent Variable: FAC3_1						

Source; Researcher's estimate with SEM, 2022. Factor score3 for analysis1 (FAC3_1) represents FINC component measure of people with active bank accounts. Factor score 1 for analysis5 (FAC1_5) connotes AIEFD component that measures AI ability to alert customers when their accounts are being compromised

The bivariate analysis of the relationship between AI enabled fraud detection (AIEFD) and financial inclusion (FINC) is as presented in Table (4.17). The result of the standardized beta coefficient (-0.064; P-value>0.05) shows the probability of having T-statistic as large as 1.187 in absolute value is above 0.05 level. This implies the factor regression of AIEFD component (FAC1_5) in the prediction of FINC is not significantly different from zero at 5 percent level. It thus suggests that there is an inverse relationship between AIEFD and FINC though not statistically significant. The model overall goodness of fit information is seen to be statistically indifferent from zero at 5 percent significant level.

AI-Enabled Personalised Banking and Automation

The items used to measure artificial intelligence enabled personalised banking and automation (AIPBA) are AI proficiency in collating and sending of monthly updates on customers' banking transaction for a particular month (AIPBA_1), management of large volume of customers data without any error (AIPBA_2), sending transaction notification s to customers on real-time basis (AIPBA_3), informing customer of the availability of banking tools such as tokens, debits and credit cards (AIPBA_4), suggestions on relevant banking solutions to individuals and business based on their transaction data (AIPBA_5), smart banking advice to customers (AIPBA_6), alerting customers to suspicious transactions conducted on their account (AIPBA_7), blocking of transactions that do not align with customers' standing orders on their accounts (AIPBA_8), provision of historical data on transactions for customers (AIPBA_9) and sending follow-up messages on customers' recent transactions (AIPBA_10).

Table 4: Factor Analysis of AI-Enabled Personalised Banking and Automation

Factor Analysis of AI-Enabled Personalised Banking and Automation						
	Rotated Component Matrix					**Communalities**
	1	2	3	4	Initial	Extraction
AIPBA _1	.879	-.048	-.095	-.028	1.000	.785
AIPBA _2	.901	.000	-.128	-.092	1.000	.837
AIPBA _3	.638	.216	.300	-.331	1.000	.653
AIPBA _4	.115	.108	.803	-.280	1.000	.749
AIPBA _5	-.233	-.077	.826	.266	1.000	.812
AIPBA _6	-.211	-.091	.238	.832	1.000	.802
AIPBA _7	-.065	.106	-.319	.790	1.000	.742
AIPBA _8	.055	.555	-.446	.344	1.000	.629
AIPBA _9	.006	.935	.019	-.049	1.000	.876
AIPBA _10	.030	.894	.070	-.038	1.000	.807
Initial Eigen values (Cum%)	26.153	47.823	66.007	76.930	10.000	7.692

Measure of Sampling Adequacy		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy		0.587
	Approx. Chi-Square	1367.747
Bartlett's Test of Sphericity	df	45
	Sig.	.000
Extraction Method: Principal Component Analysis Rotation Method: Varimax with Kaiser Normalization		
a. Rotation converged in 5 iterations		

Source; Researcher's estimate with SEM, 2022

The KMO test for appropriateness of the sample by measuring the proportion of the variance in the variables that could be traced to underlying factor confirmed positive with a sampling adequacy of 0.5877, with chi-square distribution of 1367.747. Bartlett's sphericity test of uncorrelated variables with degree of freedom of 45 is significant at 1 percent level. Table 4.11 shows the initial communalities of 1 for all the measures of AIPBA suggesting the variance explained in each variable that is explained by all the components in the measurement. The extracted communalities of the principal component analysis show the corresponding variance for each of the variables being explained by its own components with AIPBA_2(0.837) as the highest variance extract in the construct measurement. The result indicates that all the extracted components were satisfactorily loaded this stage.

In order to obtain a better distribution of the variance extraction, the study further employed the rotated component matrix which shows the reduced components based on total variance explained by the eigen-values. In this case four components of AIPBA selected by the rotated component matrix are interpreted. It is observed that component_1 is highly correlated with AIPBA_2(0.901), component_2 has a high level of correlation with AIPBA_9(0.935) while AIPBA_9(0.935) on itself is not highly correlated with other components. The third component is seen to be strongly correlated with AIPBA_5(0.826) and the fourth component mostly corrected with AIPBA_6(0.832). As shown in the initial eigen-values score (Table 4.11), these four components accounted for the greatest percentage (76.93%) of variance explained in AIPBA construct for measurement of artificial intelligence.

Table 5: AI-Enabled Personalised Banking Automation and Financial Inclusion Coefficients

AI-Enabled Personalised Banking Automation and Financial Inclusion Coefficients						
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	.000	.054		-.007	.995
	FAC3_3	.100	.054	.100	1.843	.066
	F-statistic (3.373; P-value =0.066)					
	Durbin Watson =1.90					
a. Dependent Variable: FAC3_1						

Source; Researcher's estimate with SEM, 2022. Factor score3 for analysis1 (FAC3_1) represents FINC component measure of people with active bank accounts. Factor score3 for analysis3 (FAC3_3) signifies AIEPBA component that measures AI sending notifications on relevant banking solutions to individuals and businesses on real time basis.

The bivariate analysis of the impact of AI enabled personalised automation on financial inclusion was estimated in Table 4.15. The estimated standardized coefficient for the factor regression score3 (FAC3_3) of the third analysis (AIPBA) shows the probability of having T-statistic as large as 1.843 in absolute value at 0.1 level (two-tailed). This implies the regression weight for AIEPBA in the prediction of financial inclusion (FINC) is significantly different from zero at 10 percent level. Further insight indicates a positive relationship between AIEPBA and FINC such that improvements in AIEPBA will translate to a proportionate positive impact on FINC. The model fitness (3.373; P-value<0.1) and absence of Durbin Watson autocorrelation bias (1.90) is an indication that the model statistically valid. Thus, AI enabled personalised automation could regarded as a significant component that facilitates financial inclusion.

4. CONCLUSION

The emergence of AI and its applications has been a game changer for many industries and societies especially those that embraced it at the early stage. AI applications have contributed to evolution of business operations, breakthroughs in specific sectors, improvement in productivity, and amelioration of environmental problems by reducing the need to use earth – destroying processes and tools, and so on. It can be said that AI applications are adaptable to almost all spheres of life and endeavours. Despite the capabilities of AI applications, there are still some pressing problems that need immediate interventions. One of these problems is financial exclusion. Many people, especially rural dwellers, small and medium enterprise in developing countries are financially excluded.

Acknowledgments
The Covenant University Centre for Research, Innovation, and Discovery (CUCRID) provided financial assistance for the study's publication, which the authors gratefully recognize. We also like to thank the Covenant University research and ethics committee for their helpful advice and kind assistance.

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