Ethical Governance, National Culture and Financial Inclusion: The Mediating Role of AI/FinTech Adoption in Nigerian Commercial Banks

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Abstract: This study examines how ethical governance and cultural factors influence AI/FinTech adoption and financial inclusion in Nigerian commercial banks. Drawing on the Technology Acceptance Model and Task-Technology Fit perspective, the study argues that ethical and cultural conditions shape AI/FinTech adoption, which in turn contributes to financial inclusion. A structured questionnaire was administered to respondents with knowledge or experience of digital financial services in the Nigerian banking and FinTech context, yielding 86 usable responses. Data were analysed using IBM SPSS Statistics through reliability analysis, descriptive statistics, Pearson correlation, regression analysis, and Hayes' PROCESS mediation analysis with 5,000 bootstrap samples. The results show that ethical and cultural factors significantly predict AI/FinTech adoption. AI/FinTech adoption also has a positive and significant effect on financial inclusion. Mediation analysis further shows that AI/FinTech adoption mediates the relationships between ethical factors and financial inclusion, and between cultural factors and financial inclusion. These findings suggest that ethical governance and cultural alignment do not improve financial inclusion only through direct channels; rather, their influence operates mainly by strengthening AI/FinTech adoption. The study contributes to digital finance and financial inclusion literature by identifying AI/FinTech adoption as a key mechanism linking ethical and cultural conditions to inclusive financial outcomes. The findings also suggest that banks, FinTech providers, and regulators should promote transparent, accountable, secure, and culturally responsive AI/FinTech systems to support sustainable financial inclusion.

Keywords: AI/FinTech adoption, Ethical governance, Cultural factors, Financial inclusion, Nigerian commercial banks.

1. INTRODUCTION

The past decade and a half have witnessed an unprecedented transformation in the delivery of financial services, driven by the rapid proliferation of financial technology (fintech). Emerging economies characterised by large unbanked populations, weak brick-and-mortar banking infrastructure, and increasingly pervasive mobile phone penetration have become both laboratories and beneficiaries of this revolution (Demirgüç-Kunt *et al*., 2021; Suri & Jack, 2016). Financial inclusion—defined as access to and usage of affordable, appropriate financial services by all members of society, especially the poor and marginalised has long been recognised as a critical enabler of poverty reduction, women's empowerment, and economic resilience (Bank, 2022). The Global Findex Database 2021 reported that the share of adults with an account in developing economies rose from 54% in 2014 to 71% in 2021, with digital payments accounting for much of this gain (Demirgüç-Kunt *et al*., 2021). However, aggregate figures mask substantial heterogeneity across countries, regions, and demographic groups. This variability suggests that technology alone is insufficient; institutional, regulatory, social, and cultural contexts profoundly mediate fintech's inclusive potential.

The adoption of fintech in emerging economies has been propelled by a confluence of supply-side and demand-side factors. On the supply side, declining costs of mobile handsets and data, cloud computing, and application programming interfaces (APIs) have enabled new entrants—fintech startups, telecom companies, and big tech firms to offer financial services at marginal costs far below those of traditional banks (Khera *et al*., 2022; Manyika *et al*., 2016). On the demand side, the unmet need for basic transaction, savings, and credit services among the 1.7 billion unbanked adults has created a vast market opportunity (Demirgüç-Kunt *et al*., 2021). Government policies have also played a catalytic role. India's Jan Dhan Yojana scheme, Aadhaar digital identity, and the Unified Payments Interface (UPI) infrastructure collectively created a public digital goods ecosystem that accelerated fintech adoption (Khera *et al*., 2022). Similarly, Kenya's early regulatory forbearance allowed Safaricom to launch M-Pesa without a banking license, demonstrating that proportional regulation can foster innovation (Jack & Suri, 2011). In contrast, countries with restrictive or uncertain regulatory environments have seen slower fintech diffusion (Zetzsche, 2017).

Nigeria provides an important context for examining these issues because digital financial services have expanded rapidly, yet financial exclusion, weak trust in formal institutions, data privacy concerns, and uneven digital literacy remain important barriers. From this perspective, the adoption of AI-enabled and FinTech-based financial services cannot be seen solely

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in terms of the availability of technology. Rather, acceptance is determined by whether users believe digital money is trustworthy, ethically managed, culturally acceptable, and valuable for enhancing access to financial services. This makes Nigeria an appropriate context for investigating how ethical and cultural factors influence AI/FinTech adoption, and how adoption leads to financial inclusion.

National ethics refers to shared normative principles that guide judgments of right and wrong within a society—encompassing trust, tolerance for corruption, religious morality, and fairness norms (Hofstede, 2001; Inglehart & Baker, 2000). Culture comprises the collective programming of the mind that distinguishes members of one group from another, including values such as uncertainty avoidance, individualism–collectivism, masculinity–femininity, long-term orientation, and indulgence (Hofstede, 2001; House *et al*., 2004). In the context of fintech and financial inclusion, ethics and culture can influence adoption at multiple levels: individual (propensity to trust digital platforms), organisational (how fintech firms design products), and institutional (regulatory philosophy, enforcement, and corruption). Yet, the dominant literature on fintech adoption has been heavily influenced by universalist technology acceptance models (TAM, UTAUT) that treat psychological and social factors as generic, rather than culturally specific (Tarhini *et al*., 2017).

A small but growing number of studies have begun to incorporate cultural variables. Rawat *et al*. (2025) used Hofstede’s dimensions to explain cross-country differences in digital financial service adoption, finding that individualism and low uncertainty avoidance positively correlated with fintech usage. Hamza *et al*. (2025) reported that long-term orientation and indulgence (as opposed to restraint) significantly influenced fintech adoption in OECD countries, and they argued that similar effects should hold for emerging economies. Idrees and Ullah (2024) compared Islamic and conventional bank customers in Pakistan, showing that religious identity moderated the effect of trust on fintech adoption. However, most studies either include culture as a set of control variables without theoretical integration or treat it as a post-hoc explanation for unexpected findings. Similarly, while ethical concerns such as transparency, privacy, fairness and accountability are increasingly recognised in digital finance, limited empirical evidence explains how ethical governance shapes AI/FinTech adoption and how this adoption translates into financial inclusion.

This paper argues that ethical governance and cultural factors are not peripheral background conditions; they are important antecedents of AI/FinTech adoption. It further argues that AI/FinTech adoption is the mechanism through which ethical and cultural conditions contribute to financial inclusion. This is important because digital financial inclusion does not occur automatically when technology is introduced. Users must trust the technology, perceive it as fair and secure, and regard it as compatible with their social and cultural context. Accordingly, the study examines whether ethical and cultural factors influence AI/FinTech adoption and whether AI/FinTech adoption mediates the relationship between these factors and financial inclusion in Nigerian commercial banks.

The study contributes to the literature in three ways. First, it extends research on technology acceptance and financial inclusion by positioning ethical and cultural factors as key antecedents to AI/FinTech adoption. Second, it provides empirical evidence from Nigeria, an emerging economy where digital financial innovation has expanded but inclusion challenges remain substantial. Third, it clarifies the mechanism linking ethics, culture, adoption, and inclusion by testing the mediating role of AI/FinTech adoption. The findings, therefore, offer both theoretical and practical insights into how digital finance can become more inclusive when supported by ethical governance and cultural alignment.

The remainder of the paper is organised as follows. Section 2 reviews the relevant literature and develops the hypotheses. Section 3 describes the research design, measurement, and data analysis procedures. Section 4 presents the empirical results. Section 5 discusses the findings. Section 6 presents limitations and future research directions. Section 7 concludes the study.

2. LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

2.1. Ethical Factors and AI/FinTech Adoption

Ethical considerations are emerging as critical determinants of fintech’s effectiveness. Transparency, fairness, privacy, accountability, and trust are all examples of ethical governance in artificial intelligence-powered financial services (Arner *et al*., 2019; Bazarbash, 2019; Gomber *et al*., 2018). These features are especially significant because financial technologies handle sensitive personal and financial data and rely heavily on automated decision-making. When people are unsure about how their data is utilized, algorithmic judgments are made, or inaccuracies might be contested, adoption may suffer (Davis, 1989; Venkatesh *et al*., 2012).

Responsible digital finance requires robust governance measures to safeguard users and mitigate exclusionary risks. Previous research suggests that FinTech can promote financial inclusion, but only when it is accompanied by adequate safeguards, regulatory clarity, data protection, and fair lending practices (Gomber *et al*., 2018; Sahay *et al*., 2020). Ethical considerations are especially important in AI-based financial services since algorithmic decisions can influence credit access, fraud detection, client profile, and service eligibility (Mhlanga, 2020). Without transparency and accountability, AI/FinTech systems may perpetuate current imbalances or undermine public trust in digital financial services.

According to the Technology Acceptance Model, people are more likely to adopt technologies that they consider beneficial, trustworthy, and simple to use (Davis, 1989). In this study, ethical governance is viewed as a precondition for AI/FinTech adoption, as trust, fairness, privacy protection, and accountability influence users' willingness to adopt digital financial technologies. In the Nigerian banking sector, where concerns about fraud, data misuse, and institutional trust may affect the use of digital finance, ethical governance is likely to play a critical role.

Therefore, the study proposes:

H1: Ethical factors are positively associated with AI/FinTech adoption.

2.2. Cultural Factors and AI/FinTech Adoption

Culture refers to shared values, beliefs, norms, and behavioural expectations that shape how individuals and organisations respond to uncertainty, authority, innovation, and change (Hofstede, 2001; House *et al*., 2004). In the context of AI/FinTech adoption, cultural factors may influence whether users trust digital platforms, accept automated decision-making, prefer traditional banking relationships, or rely on community and institutional approval before adopting new financial technologies.

A growing body of research examines how culture influences digital financial adoption. According to Hofstede's cultural aspects, uncertainty avoidance, individualism, power distance, long-term orientation, and indulgence may influence the acceptance and usage of financial technologies (Liaqat *et al*., 2022; Sahibzada Muhammad, Aysan, & Kayani, 2025). Individuals in high-uncertainty-avoidance situations, for example, may be more hesitant to adopt new financial technologies, whereas cultures with greater faith in authority or a longer-term planning orientation may respond differently to digital financial services (Wang, 2025).

The role of culture is especially important in emerging nations, because adoption decisions may not be wholly individual (Steers *et al*., 2008). They can be influenced by family expectations, community standards, religious or moral ideals, trust in formal institutions, and risk perceptions. Cultural alignment can make digital financial services more acceptable, whereas cultural opposition or ambiguity can hinder acceptance. This is consistent with technology acceptance research, which acknowledges that social influence, conducive conditions, and contextual factors influence users' behavioural intentions and technology use (Venkatesh, Thong, & Xu, 2012).

Accordingly, the study proposes:

H2: Cultural factors are positively associated with AI/FinTech adoption.

2.3. AI/FinTech Adoption and Financial Inclusion

Financial inclusion—the provision of affordable and accessible financial services to all segments of society—remains a persistent challenge in emerging economies, where large populations remain outside the formal financial system (Demirgüç-Kunt *et al*., 2021). The growth of financial technology has been viewed as a transformative force capable of bypassing traditional banking infrastructure and reaching unbanked and underbanked populations. Mobile money, digital lending platforms, blockchain technologies, and AI-driven credit scoring have increasingly advanced financial inclusion in emerging markets, with research focusing on mobile banking, peer-to-peer lending, digital payments, and data-driven financial services (Ozili, 2018; Sahay *et al*., 2020; Suri & Jack, 2016).

AI-powered FinTech solutions are rapidly transforming financial services in emerging markets. These applications include machine learning-based credit scoring, automated fraud detection, customer profiling, digital lending, robo-advisory services, regtech tools, and AI-powered risk assessment. AI-based credit scoring is especially significant in emerging nations, where many individuals and small firms do not have established credit records. AI-driven models can support more inclusive credit assessment and provide financial services to underserved customers by utilizing alternative data such as mobile phone usage, digital transaction records, utility payments, and behavioral data (Bazarbash, 2019; Biallas & O'Neill, 2020; Cao *et al*., 2021). However, these applications also raise concerns about algorithmic opacity, data privacy, bias, consumer protection, and explainability, making ethical governance central to sustainable AI/FinTech adoption (Financial Stability Board, 2017; Sahay *et al*., 2020).

However, the realisation of fintech's inclusive potential is neither automatic nor uniform across contexts. A growing body of evidence suggests that the adoption and impact of fintech are critically shaped by the institutional, ethical and cultural environments in which they operate (Hamza *et al*., 2025; Liaqat *et al*., 2022). While much of the existing literature has focused on supply-side factors – digital infrastructure, regulatory frameworks, and economic conditions less attention has been given to how ethical governance and cultural factors shape AI/FinTech adoption and how adoption subsequently contributes to financial inclusion. This gap is particularly important in emerging economies, where financial exclusion often reflects not only limited infrastructure but also issues of trust, risk perception, digital literacy, and institutional confidence.

Digital financial technology can help to increase inclusion by lowering transaction costs, expanding access beyond physical bank branches, enabling mobile payments, and boosting access to savings, credit, and insurance services. However, these benefits are contingent on whether individuals and organizations accept such technologies. As a result, AI/FinTech adoption becomes a key mechanism for transforming digital financial innovation into inclusion outcomes. Adoption may be especially crucial for Nigerian commercial banks because digital finance can help reach underserved customers, but only if users trust the system and believe it is relevant, secure, and accessible.

Based on this argument, the study proposes:

H3: AI/FinTech adoption is positively associated with financial inclusion.

2.4. Mediating Role of AI/FinTech Adoption

Although earlier research has focused on the direct relationship between FinTech and financial inclusion, the mechanism by which ethical and cultural variables contribute to inclusion has received less attention (Arner *et al*., 2019; Sahay *et al*., 2020). Ethical governance and cultural alignment may not promote financial inclusion without first promoting the use of AI/FinTech services. For example, clear data practices and culturally suitable digital interfaces may boost confidence and acceptability, leading to increased adoption of digital financial services (Venkatesh *et al*., 2012). In this approach, adoption serves as the conduit through which ethical and cultural factors shape inclusive outcomes.

This argument aligns with the Technology Acceptance Model (TAM) and the Task-Technology Fit approach. TAM explains why people embrace or reject technologies based on perceived usefulness and perceived ease of use Davis (1989), whereas Task-Technology Fit posits that technology is more likely to improve results when it meets user demands and task requirements (Goodhue & Thompson, 1995). These ideas, taken together, imply that ethical and cultural considerations shape the adoption environment, while adoption itself carries their effects through to financial inclusion outcomes.

This approach is significant for Nigerian commercial banks, as digital financial inclusion is determined not only by the availability of AI/FinTech services but also by whether consumers adopt and use them. Ethical governance may boost trust, whilst cultural alignment may lessen opposition and increase relevance. As use grows, financial institutions may be able to improve access, usage, savings, credit outreach, payments, and other inclusive financial services.

Therefore, the study proposes:

H4: AI/FinTech adoption mediates the relationship between ethical/cultural factors and financial inclusion.

2.5. Conceptual Framework

Figure **1** presents the conceptual framework of the study. The framework posits that ethical and cultural factors serve as antecedents to AI/FinTech adoption. AI/FinTech adoption, in turn, is expected to improve financial inclusion. The framework further proposes that AI/FinTech adoption mediates the relationship between ethical/cultural factors and financial inclusion.

3. METHODOLOGY

3.1. Research Design and Sample

This study employed a quantitative survey design to examine the relationships among ethical factors, cultural factors, AI/FinTech adoption, and financial inclusion in Nigerian commercial banks. A survey design was appropriate because the study aimed to test hypothesised relationships using measurable perceptions of AI/FinTech adoption and financial inclusion. The study followed a deductive approach, as the proposed relationships were developed from technology acceptance, task-technology fit, and digital financial inclusion literature.

Data were collected through an online structured questionnaire. The target respondents included individuals with knowledge or experience of AI/FinTech-related financial services in Nigerian commercial banking and FinTech contexts, including banking professionals, FinTech users, and customers

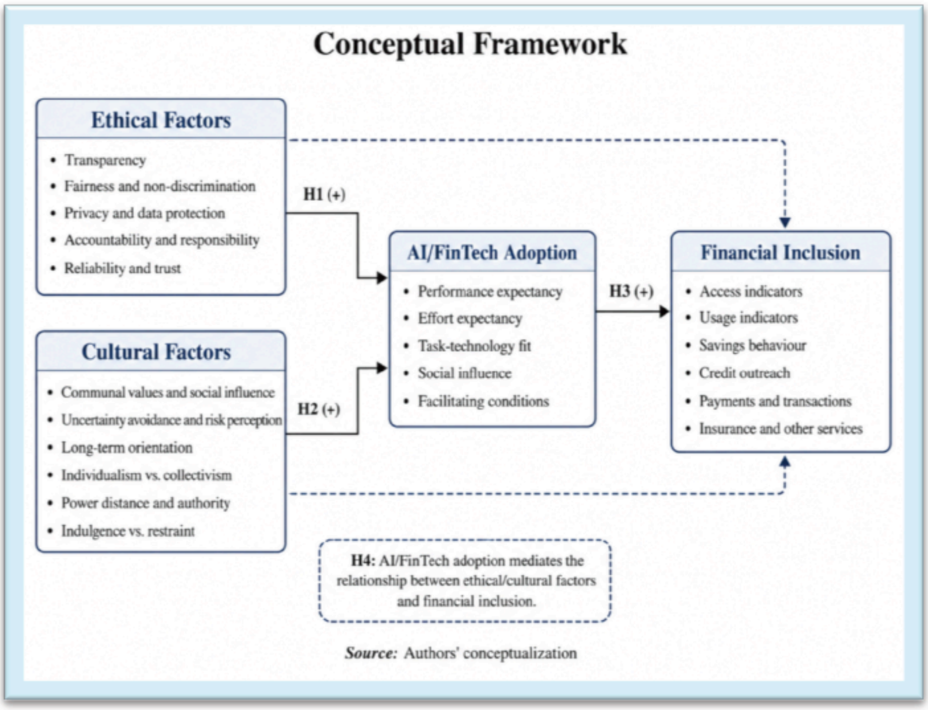

Figure 1: Conceptual Framework.

of digital financial services. A purposive sampling approach was used to ensure that respondents had relevant exposure to the study context. After screening the responses, 86 usable observations were retained for analysis.

3.2. Measurement of Variables

The questionnaire examined four key constructs: ethical factors, cultural factors, AI/FinTech adoption, and financial inclusion. All construct items were scored on a five-point Likert scale, from 1 (strongly disagree) to 5 (strongly agree). Transparency, fairness, privacy and data protection, accountability, and trust were among the ethical aspects assessed. Cultural characteristics included communal ideals, uncertainty avoidance, long-term orientation, individualism/collectivism, power distance, and restraint. AI/FinTech adoption was evaluated using performance expectation, effort expectancy, task-technology fit, social influence, and facilitating factors. Financial inclusion was assessed by access, utilization, savings behavior, credit outreach, payments and transactions, and insurance/other financial services. Composite scores were created by averaging the relevant items for each construct. This approach retained the original five-point scale and allowed direct interpretation of the variables.

3.3. Data Analysis

The data were analysed with IBM SPSS Statistics. The analysis was conducted in five steps. First, the data were cleaned, and the Likert-scale responses were categorised as 1-5. Second, Cronbach's alpha was utilised to assess the internal consistency of the measurement scales. Third, descriptive statistics and Pearson correlations were employed to investigate the variables' distribution and initial relationships. Fourth, multiple regression analysis was utilised to investigate the direct links between ethical and cultural factors, AI/FinTech adoption, and financial inclusion. Finally,

Table 1: Measurement of Study Variables

Construct	Role in model	Measurement
Ethical Factors	Independent variable	Mean score of items on transparency, fairness, privacy, accountability, and trust
Cultural Factors	Independent variable	Mean score of items on social influence, uncertainty avoidance, long-term orientation, individualism, power distance, and restraint
AI/FinTech Adoption	Mediating variable	Mean score of items on perceived usefulness, ease of use, task-technology fit, social influence, and facilitating conditions
Financial Inclusion	Dependent variable	Mean score of items on access, usage, savings, credit outreach, payments, and insurance/other services

mediation analysis was conducted using Hayes' PROCESS Macro Model 4 with 5,000 bootstrap samples and 95% confidence intervals (Hayes, 2015).

The following regression models were estimated:

$$FA = \alpha + \beta_1 ETHICS + \beta_2 CULTURE + \varepsilon \tag{1}$$

$$FI = \alpha + \beta_1 FA + \varepsilon \tag{2}$$

$$FI = \alpha + \beta_1 ETHICS + \beta_2 CULTURE + \beta_3 FA + \varepsilon \tag{3}$$

where FA represents AI/FinTech adoption, and FI represents financial inclusion. The mediation analysis tested whether AI/FinTech adoption carries the effects of ethical and cultural factors on financial inclusion. The indirect effect was considered significant when the 95% bootstrap confidence interval did not include zero.

3.4. Ethical Considerations

Participation in the study was voluntary, and respondents were informed that the survey was for academic research purposes. The questionnaire did not collect personally identifiable information, and all responses were treated anonymously and confidentially. The data were stored securely and used only for research analysis.

4. RESULTS

4.1. Respondents Demographics

Table **2** shows the demographic characteristics of the respondents. The final sample consisted of 86 respondents. Most respondents (55.8%) were between the ages of 26 and 35, with the 36-45 age group coming in second (26.7%). Female respondents made up 62.8% of the sample, with male respondents accounting for 37.2%. In terms of educational background, many respondents (47.7%) had a bachelor's degree, followed by postgraduate qualifications (33.7%) and diploma/vocational credentials (17.4%). In terms of occupational roles, mid-level management (31.4%) was the largest group, followed by entry-level personnel (24.4%), IT/technical staff (16.3%), customer service staff (14.0%), senior management (11.6%), and executive/C-suite respondents (2.3%). Overall, the sample comprises respondents with relevant educational and

Table 2: Demographic Profile of Respondents

Demographic variable	Category	Frequency	Percentage
Age	Not specified	1	1.2
	18–25	6	7.0
	26–35	48	55.8
	36–45	23	26.7
	46–55	6	7.0
	56–65	2	2.3
	Total	86	100.0
Gender	Female	54	62.8
	Male	32	37.2
	Total	**86**	**100.0**
Education	Secondary school	1	1.2
	Diploma/Vocational	15	17.4
	Bachelor's degree	41	47.7
	Postgraduate degree	29	33.7
	Total	**86**	**100.0**
Role	Customer service	12	14.0
	Entry-level employee	21	24.4
	Executive/C-suite	2	2.3
	IT/Technical staff	14	16.3
	Mid-level management	27	31.4
	Senior management	10	11.6
	Total	**86**	**100.0**

Note: One respondent did not specify age.

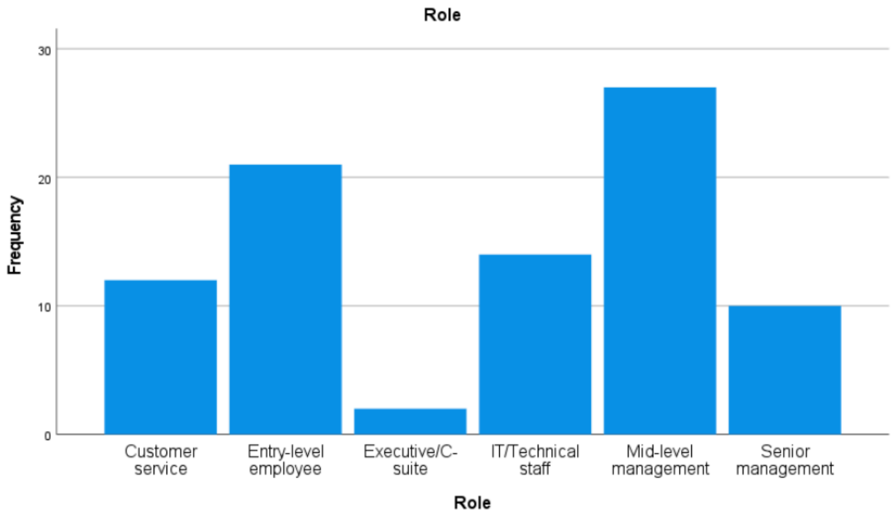

Figure 2: Distribution of respondents by organisational role.

organisational backgrounds for research on AI/FinTech adoption and financial inclusion.

4.2. Measurement Reliability

The reliability results in Table **3** indicate that all study constructs achieved acceptable to excellent internal consistency, with Cronbach's alpha values ranging from 0.789 to 0.916. These results confirm that the items used to measure ethical factors, cultural factors, AI/FinTech adoption, and financial inclusion are sufficiently reliable for subsequent correlation, regression, and mediation analyses.

4.3. Descriptive Statistics and Correlation Matrix

Table **4** shows the descriptive statistics and Pearson correlation coefficients for the main study variables. The results demonstrate that all variables have positive and statistically significant associations. Ethical aspects are positively correlated with AI/FinTech adoption ($r = .621$, $p < .001$) and financial inclusion ($r = .410$, $p < .001$). Cultural factors are positively associated with AI/FinTech adoption ($r = .575$, $p < .001$) and financial inclusion ($r = .362$, $p < .001$). Adoption of AI/FinTech is associated with greater financial inclusion ($r = .487$, $p < .001$). These findings give preliminary support for the hypothesised relationships prior to regression analysis.

4.4. Regression Analysis

Table **5** presents the regression results for the hypothesised relationships among ethical factors, cultural factors, AI/FinTech adoption, and financial inclusion. Model 1 shows that ethical and cultural

Table 3*:* **Reliability Analysis**

Construct	Items	Valid N	Cronbach's Alpha	Interpretation	Decision
Ethical Factors	10	83	0.816	Good	Retain all items
Cultural Factors	12	86	0.789	Acceptable	Retain all items
AI/FinTech Adoption	10	83	0.866	Good	Retain all items
Financial Inclusion	17	80	0.916	Excellent	Retain all items

Table 4*:* **Descriptive Statistics and Correlations**

Variable	Mean	SD	1	2	3	4
1. Ethical Factors	3.89	0.56	1			
2. Cultural Factors	4.03	0.47	.640**	1		
3. AI/FinTech Adoption	4.13	0.49	.621**	.575**	1	
4. Financial Inclusion	3.75	0.61	.410**	.362**	.487**	1

Note: N = 86. **p** < .01, two-tailed.

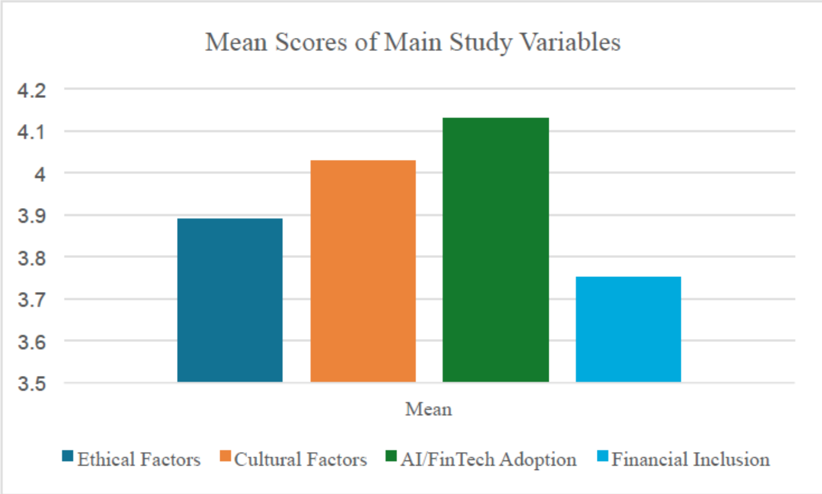

Figure 3: Mean scores of ethical factors, cultural factors, AI/FinTech adoption and financial inclusion.

Table 5: Regression Results

Predictor	Model 1: FA	Model 2: FI	Model 3: FI
Ethical Factors	0.378***	—	0.160
Cultural Factors	0.312**	—	0.078
AI/FinTech Adoption	—	0.605***	0.449**
Constant	1.410***	1.244*	0.953
R^2	0.439	0.238	0.258
Adjusted R^2	0.425	0.229	0.231
F-statistic	32.452***	26.181***	9.517***
Durbin-Watson	2.210	1.783	1.821
N	86	86	86

Note: Entries are unstandardised regression coefficients. FA = AI/FinTech Adoption; FI = Financial Inclusion. *p < .05, **p < .01, ***p < .001.

factors jointly have a positive and significant effect on AI/FinTech adoption (F = 32.452, p < .001), explaining 43.9% of the variance in adoption. Ethical factors are positively associated with AI/FinTech adoption (B = .378, p < .001), while cultural factors are also positively and significantly associated (B = .312, p < .01). These results indicate that both ethical governance and cultural alignment are important antecedents of AI/FinTech adoption.

Model 2 examines the direct effect of AI/FinTech adoption on financial inclusion. The model is statistically significant (F = 26.181, p < .001) and explains 23.8% of the variance in financial inclusion. AI/FinTech adoption has a positive and significant effect on financial inclusion (B = .605, p < .001), indicating that higher AI/FinTech adoption is associated with stronger financial inclusion outcomes.

Model 3 includes ethical and cultural factors, as well as AI/FinTech adoption, as predictors of financial inclusion. The model remains statistically significant (F = 9.517, p < .001) and explains 25.8% of the variance in financial inclusion. AI/FinTech adoption stays positive and significant (B = .449, p < .01), while ethical factors (B = .160) and cultural factors (B = .078) are not significant direct predictors. This suggests that ethical and cultural factors contribute to financial inclusion primarily by supporting AI/FinTech adoption, rather than through a direct pathway.

4.5. Mediation Analysis

Table **6** presents the bootstrapped mediation results for the indirect effects of ethical and cultural factors on financial inclusion through AI/FinTech adoption. The indirect effect of ethical factors on financial inclusion through AI/FinTech adoption is positive and significant (B = .2581, BootSE = .0802, 95% CI [.1012, .4176]). Since the confidence interval does not include zero, the result supports the mediating role of AI/FinTech adoption in the relationship between ethical factors and financial inclusion.

Similarly, the indirect effect of cultural factors on financial inclusion through AI/FinTech adoption is

Table 6: Bootstrapped Mediation Results

Mediation path	Total effect	Direct effect	Indirect effect	Boot SE	95% Boot LLCI	95% Boot ULCI	Decision
ETHICS → FA → FI	.4491***	.1910	.2581	.0802	.1012	.4176	Supported
CULTURE → FA → FI	.4656***	.1573	.3082	.1177	.1090	.5719	Supported

Note: FA = AI/FinTech Adoption; FI = Financial Inclusion. Bootstrap samples = 5,000. Direct and total effects are unstandardised coefficients. Indirect effects are significant when the 95% bootstrap confidence interval does not include zero. ***p < .001.

positive and significant (B = .3082, BootSE = .1177, 95% CI [.1090, .5719]). This confirms that AI/FinTech adoption also mediates the relationship between cultural factors and financial inclusion. Overall, the mediation results suggest that ethical and cultural factors improve financial inclusion indirectly by strengthening AI/FinTech adoption.

4.6. Exploratory Sub-Construct Analysis

4.6.1. Ethical sub-constructs' effect on AI/FinTech adoption

To provide further insight into the ethical drivers of AI/FinTech adoption, an exploratory regression was conducted using the five ethical sub-constructs as predictors. Results in Table **7** show that among the ethical dimensions, accountability had a positive and significant effect on AI/FinTech adoption, followed by trust. Transparency, fairness, and privacy were positive but not statistically significant. These findings suggest that accountability and trust are the most salient ethical conditions supporting AI/FinTech adoption in this sample.

4.6.2. Cultural sub-constructs' effect on AI/FinTech adoption

An exploratory regression was also used to determine which cultural sub-constructs are most strongly connected with AI/FinTech adoption. Table **8** reports that restraint had the strongest positive association with AI/FinTech adoption, followed by power distance/authority and individualism. Neither communal values nor long-term orientation was an important predictor. Uncertainty avoidance showed a marginal negative association, suggesting that heightened risk concerns may impede AI/FinTech adoption. However, this effect did not approach the 5% significance threshold. Overall, the results suggest that

Table 7: Exploratory Regression of Ethical Sub-Constructs on AI/FinTech Adoption

Predictor	B	SE	β	t-value	p-value	VIF
Transparency	.052	.058	.097	.888	.377	1.699
Fairness	.048	.068	.078	.712	.478	1.681
Privacy	.059	.079	.078	.741	.461	1.577
Accountability	.223	.067	.355	3.335	.001	1.605
Trust	.189	.067	.266	2.814	.006	1.270
Constant	1.908	.329	—	5.807	< .001	—

Model statistics: R^2 = .435; Adjusted R^2 = .400; F(5, 80) = 12.322, p < .001; N = 86.
Note: Dependent variable = AI/FinTech Adoption. Entries are unstandardised coefficients. VIF = variance inflation factor.

Table 8: Exploratory Regression of Cultural Sub-Constructs on AI/FinTech Adoption

Predictor	B	SE	β	t-value	p-value	VIF
Communal values/social influence	.049	.075	.065	.657	.513	1.427
Uncertainty avoidance/risk perception	-.120	.063	-.190	-1.910	.060	1.432
Long-term orientation	.048	.090	.056	.536	.594	1.575
Individualism	.146	.056	.253	2.594	.011	1.383
Power distance/authority	.248	.089	.287	2.794	.007	1.531
Restraint	.249	.072	.363	3.464	< .001	1.592
Constant	1.607	.387	—	4.154	< .001	—

Model statistics: R^2 = .456; Adjusted R^2 = .415; F(6, 79) = 11.033, p < .001; N = 86.
Note: Dependent variable = AI/FinTech Adoption. Entries are unstandardised coefficients. VIF = variance inflation factor.

Hypothesis	Statement	Decision
H1	Ethical factors positively influence AI/FinTech adoption.	Supported
H2	Cultural factors positively influence AI/FinTech adoption.	Supported
H3	AI/FinTech adoption positively influences financial inclusion.	Supported
H4	AI/FinTech adoption mediates the relationship between ethical/cultural factors and financial inclusion.	Supported

culturally grounded trust in authority, self-directed financial decision-making, and restraint-oriented financial behaviour are particularly relevant for AI/FinTech adoption.

4.7. Summary of Hypotheses

Overall, the findings support the proposed relationships. Ethical and cultural factors significantly predict AI/FinTech adoption, while AI/FinTech adoption, in turn, significantly predicts financial inclusion. The mediation results further show that AI/FinTech adoption carries the effects of ethical and cultural factors on financial inclusion. Thus, the results support the argument that ethical governance and cultural alignment are important enabling conditions for AI/FinTech adoption, which in turn strengthens financial inclusion.

5. DISCUSSION

The findings indicate that ethical governance and cultural characteristics are major predictors of AI/FinTech adoption, and that AI/FinTech adoption is the primary mechanism by which these factors contribute to financial inclusion. This shows that the adoption of AI/FinTech in Nigerian commercial banks is influenced not only by technological readiness but also by users' perceptions of digital financial systems as trustworthy, fair, safe, accountable, and culturally appropriate. This is consistent with the Technology Acceptance Model, which contends that technology adoption is determined by users' perceptions of usefulness and ease of use (Davis, 1989), as well as the Task-Technology Fit perspective, which contends that adoption is increased when technology meets users' needs and task requirements (Goodhue & Thompson, 1995).

The positive impact of ethical considerations on AI/FinTech adoption suggests that transparency, fairness, privacy, accountability, and trust are critical to the acceptability of digital finance. Because financial technologies require users to exchange sensitive personal and financial information, concerns about data privacy, algorithmic fairness, and accountability may affect adoption decisions. This complements earlier research arguing that responsible digital banking necessitates governance structures that safeguard consumers, decrease exclusionary risks, and boost trust in digital financial systems (Arner *et al*., 2019; Gomber *et al*., 2018). As a result, the findings show that ethical AI governance should be viewed as a prerequisite for successful AI/FinTech adoption, rather than merely a compliance requirement.

The results also reveal that cultural factors have a substantial impact on AI/FinTech adoption. This implies that social values, trust in authority, uncertainty avoidance, community influence, and long-term orientation influence how users interact with digital financial technologies. Adoption decisions in emerging economies may be influenced by societal norms, risk perceptions, trust in formal institutions, and individual views. This finding is consistent with Hofstede's cultural theory, which states that cultural values influence responses to uncertainty, authority, innovation, and change (Hofstede, 2001). It also lends support to previous research indicating that cultural factors influence digital finance adoption and financial inclusion results (Liaqat *et al*., 2022; Venkatesh *et al*., 2012).

AI/FinTech adoption is found to have a positive and significant effect on financial inclusion. This implies that greater use of AI/FinTech is linked to increased access to financial services, increased use of digital transactions, enhanced savings and credit outreach, and better service provision for underprivileged groups. This finding is consistent with the larger financial inclusion literature, which indicates that digital payments, mobile banking, and fintech platforms can lower entry barriers and increase financial participation in emerging and developing economies (Demirgüç-Kunt *et al*., 2021; Suri & Jack, 2016). In the Nigerian context, this implies that AI/FinTech can promote inclusion by expanding access to financial services beyond traditional branch-based banking channels.

The study's main contribution is its mediation results. AI/FinTech adoption acts as a bridge between ethical and cultural factors in the context of financial inclusion. When it comes to adoption, ethical and cultural factors do not directly translate into financial inclusion. Instead, they promote inclusiveness indirectly by increasing AI/FinTech usage. This research emphasizes how ethics and culture interact: ethical governance and cultural alignment foster an atmosphere conducive to adoption, which then serves as a channel for improving financial inclusion.

The study theoretically advances research on technology acceptance and financial inclusion by demonstrating that AI/FinTech adoption is both a result of ethical and cultural conditions and a mechanism linking those variables to inclusive financial outcomes. Existing research frequently treats fintech adoption as a direct driver of financial inclusion or investigates ethics and culture as contextual issues. This study integrates these aspects in a single pathway, demonstrating that financial inclusion is dependent not just on technological availability, but also on trust, governance, social acceptance, and user confidence (Arner *et al*., 2019; Venkatesh *et al*., 2012).

The findings have significant practical implications for Nigeria's commercial banks and FinTech firms. First, banks should incorporate ethical governance into their overall adoption strategy rather than treating it solely as a compliance issue. This necessitates explicit disclosure about how AI systems use customer data, how automated choices are produced, and how customers can appeal or challenge AI-generated outcomes. Second, FinTech companies should create culturally relevant digital services that reflect local trust norms, language preferences, digital literacy levels, and risk perceptions. This is especially crucial for rural clients, low-income groups, women, the elderly, and people who have restricted access to digital money. Third, banks and FinTech companies should invest in customer education, clear onboarding, data security safeguards, and user-friendly interfaces to minimize uncertainty and boost trust in digital financial services. These steps can assist increase AI/FinTech adoption and transfer digital innovation into greater financial inclusion outcomes.

From a policy perspective, regulators can encourage AI/FinTech use by establishing clear norms for data privacy, algorithmic transparency, consumer protection, and fairness in digital lending and automated decision-making. In emerging economies like Nigeria, inadequate ethical monitoring may erode trust and hinder the inclusive potential of digital finance. As a result, regulatory frameworks should promote innovation while ensuring that digital finance is transparent, accountable, and inclusive.

6. LIMITATIONS AND FUTURE RESEARCH

This study has some limitations that should be acknowledged. First, the sample size is relatively small, with only 86 valid responses. Although the sample size is adequate for the regression and mediation analyses conducted in this study, the results may not be fully generalizable to other Nigerian commercial banks or larger emerging market contexts. To improve generalizability, future studies should use bigger sample sizes from numerous banks, FinTech enterprises, locations, and consumer segments. Second, the study's concentration on Nigerian commercial banks limits the findings' applicability to other institutional and cultural environments. Future study should include comparative studies across emerging economies to see if ethical governance and cultural issues affect AI/FinTech adoption differentially across countries. Third, the study employs cross-sectional survey data, which reflects respondents' perceptions at a single point in time. Future research might employ longitudinal data to look at how trust, ethical perceptions, cultural alignment, and AI/FinTech adoption change over time. Finally, future research might focus on specific AI/FinTech applications, such as digital lending, AI-based credit scoring, fraud detection, robo-advisory services, and mobile banking, to better identify which technologies have the most inclusion impact.

7. CONCLUSION

This study examined the role of ethical and cultural factors in shaping AI/FinTech adoption and financial inclusion in Nigerian commercial banks. Drawing on survey data from 86 respondents, the study provides evidence that ethical governance and cultural factors are important antecedents of AI/FinTech adoption. The findings show that both ethical factors and cultural factors significantly predict AI/FinTech adoption, indicating that users' acceptance of digital financial technologies depends not only on technological readiness but also on trust, accountability, fairness, privacy, social values, and cultural alignment.

The study also concludes that AI/FinTech adoption has a positive and significant impact on financial inclusion. This implies that greater usage of AI/FinTech is linked to enhanced access to financial services, increased use of digital transactions, improved savings and credit outreach, and better financial service provision for underprivileged groups. More crucially, the mediation findings reveal that AI/FinTech adoption mediates the relationships between ethical factors and financial inclusion, and between cultural factors and financial inclusion. This suggests that ethical and cultural factors increase financial inclusion primarily by increasing AI/FinTech use, rather than through a direct channel.

The study adds to the literature by demonstrating that AI/FinTech adoption is more than just a technological outcome; it is also a vehicle via which ethical governance and cultural alignment can assist equitable financial development. In practice, the findings indicate that banks and FinTech providers should invest not only in digital infrastructure but also in transparent, accountable, secure, and culturally relevant financial systems. For policymakers and regulators, the report emphasizes the importance of clear criteria for algorithmic transparency, consumer protection, data privacy, and fairness in digital financial services.

The findings have important implications for policy and regulatory frameworks. Regulators should encourage AI and FinTech use by establishing clear standards for data privacy, algorithmic transparency, consumer protection, explainability, and fairness in automated financial decision-making. In the Nigerian context, these policies might assist to eliminate mistrust, safeguard vulnerable users, and guarantee that digital financial innovation promotes inclusion rather than exclusion. Policies should also promote responsible innovation, digital literacy, and collaboration among banks, FinTech companies, regulators, and consumer protection organizations. This can help to develop an ethical and inclusive AI/FinTech ecosystem that promotes long-term financial inclusion.

Overall, the findings suggest that financial inclusion cannot be achieved through digital technology alone. AI/FinTech can support inclusive finance, but its effectiveness depends on whether users trust these systems, perceive them as ethically governed, and consider them suitable for their cultural and social context. Future research may extend this study by using a larger sample, comparing multiple emerging economies, or examining specific AI/FinTech applications such as digital lending, mobile banking, and AI-based credit scoring.

DATA AVAILABILITY STATEMENT

Data will be made available on request.

DECLARATION OF COMPETING INTERESTS

The authors declare no conflicts of interest.

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