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DETERMINANTS OF ELECTRONIC PAYMENT SYSTEM ADOPTION IN PUBLIC HOSPITALS IN JIGAWA STATE, NIGERIA

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ABSTRACT

This study examines the factors that determine the adoption of electronic payment systems (EPS) in public hospitals in Jigawa State, Nigeria. A cross-sectional survey design was used. The population of the study comprised approximately 3,750 staff of public hospitals (tertiary, specialist, general and cottage) in the State, and a proportionately allocated sample of 361 respondents was determined with the Taro Yamane formula. Of 361 questionnaires administered, 350 were returned and 346 were usable (95.8%). Data were analysed with partial least squares structural equation modelling (PLS-SEM). Technological factors and organizational factors had significant positive effects on electronic payment system adoption, whereas environmental factors had a significant negative effect on electronic payment system adoption. The study further revealed that human factors had no significant effect on electronic payment system adoption. The study recommends reliable power and internet infrastructure, visible management commitment backed by structured staff training, and clear regulatory guidance on the use of electronic payments in public hospitals.

Key words: *Electronic payment system, HOT-fit, Jigawa State, PLS-SEM, public hospitals, technology adoption.*

Paper type: *Research paper*

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INTRODUCTION

Payment is the point at which a patient's need for care meets the hospital's ability to deliver it. In Nigeria that point is especially consequential because most people who are not covered by

the National Health Insurance Scheme pay for services out of pocket, and billing and payment typically take place on the spot before treatment is rendered (Abugu et al., 2023). How a hospital receives, records and reconciles these payments therefore affects waiting times, the integrity of revenue and, ultimately, the quality of care. Electronic payment systems (EPS), which move funds through channels such as point-of-sale (POS) terminals, mobile banking applications, online transfers and bank transfers, offer an alternative to cash and cheques. Their promised benefits are practical. They can reduce the time patients and caregivers lose queuing at pay points, operate alongside clinical services without constant human intervention, and limit the errors, fatigue and financial dishonesty associated with manual cash handling (Abugu et al., 2023). They also leave a traceable record of transactions, which strengthens financial accountability (Adeniji et al., 2025).

Nigerian policy has pointed in this direction for more than a decade. The Federal Government's cashless policy of 2012 encouraged public agencies to adopt electronic payments, and further digital payment policies have followed (Abugu et al., 2023; Adeniji et al., 2025). Nigeria's banking sector and consumer market have responded: studies of bank customers show that convenience and security shape whether people adopt electronic payment (Oyelami et al., 2020). Yet the response has not been even across institutions. Gholami et al. (2010) described Nigeria as having a low e-payment adoption rate despite the benefits and the efforts of financial authorities, and Abdurrahaman et al. (2021) showed that rural customers, who are rarely studied, face their own constraints, including the quality of internet connections. Public hospitals appear to sit at the slow end of this uneven picture. Abugu et al. (2023) observed that publicly run hospitals, as traditional bureaucratic institutions, have been slow to adjust their systems to e-payment, and that electricity, internet service, network interruption and internet fraud remain live concerns (see also Ololade et al., 2020). Adeniji et al. (2025) likewise found that, although digital payment is accepted and used in the Nigerian health sector, failed transactions, cybersecurity risks, double payments and unfriendly bank policies still hamper it.

This unevenness matters for a practical reason. A hospital that continues to rely on cash and manual records carries the costs of delay, error and leakage that electronic channels are designed to reduce, and it does so in a sector where delays can affect patients' access to treatment. It also matters for a policy reason. If the cashless agenda is to reach the institutions that serve most Nigerians, decision-makers need to know what actually separates hospitals that adopt electronic payment from those that do not. Without that knowledge, interventions risk being aimed at the wrong barrier, for instance training staff when the binding constraint is

unreliable power or connectivity, or purchasing terminals when the constraint is weak management support.

The existing evidence does not yet answer this question for public hospitals in northern Nigeria, for three reasons. First, most Nigerian research on electronic payment concerns bank customers or general consumers (Oyelami et al., 2020; Gholami et al., 2010; Abdurrahaman et al., 2021), whose decisions are voluntary and individual. A hospital's adoption is an organizational decision made within a budget, a hierarchy and a regulatory setting, so findings from consumers cannot simply be transferred. Second, the few hospital-based studies address narrower questions. Abugu et al. (2023) examined the attitudes of managerial staff in four public tertiary hospitals in Enugu, a southeastern state, and Adeniji et al. (2025) analysed the readiness of digital payment for paying health workers. Neither tested how technological, organizational, human and environmental conditions jointly shape adoption, and neither covered a northern state or the full range of hospital levels, from tertiary centres to rural cottage hospitals. Third, the factors have mostly been studied in isolation, although technology adoption research has long argued that outcomes depend on the interaction of user, organizational and technical conditions (Davis, 1989; Venkatesh et al., 2003; Yusof et al., 2008).

Jigawa State provides a suitable setting in which to address these gaps. Its public hospitals include a federal tertiary centre, a specialist hospital, general hospitals and cottage hospitals, so they differ in size, staffing and infrastructure, and this variation allows factors to be compared. Hospitals in the State are likely to operate under tighter budgets and weaker infrastructure than urban hospitals in other parts of the country, which makes the environmental and organizational conditions for adoption especially relevant. The study also addresses a theoretical gap. The Human–Organization–Technology fit (HOT-fit) model was designed for health information systems and highlights human, organizational and technological fit (Yusof et al., 2008), but it gives limited attention to the external environment, such as regulation, infrastructure and bank support, which the technology, organization, environment framework treats as a distinct determinant (Tornatzky & Fleischer, 1990). Combining the two lets the study test whether external conditions help or hinder adoption alongside the internal factors.

The problem addressed by this study is therefore the lack of empirical evidence on the combined influence of technological, organizational, human and environmental factors on the adoption of electronic payment systems in public hospitals in Jigawa State. Left unaddressed,

hospital administrators and policymakers will continue to rely on evidence drawn from banks and consumers, and efforts to promote cashless payment in public health care may be poorly targeted. The study sets out to:

i. examine the influence of technological factors on the adoption of EPS in public hospitals in Jigawa State;

ii. determine the effect of organizational factors on the adoption of EPS in public hospitals in Jigawa State;

iii. explore the effect of human factors on the adoption of EPS in public hospitals in Jigawa State; and

iv. investigate the effect of environmental factors on the adoption of EPS in public hospitals in Jigawa State.

The findings are significant to several groups. Hospital administrators can use them to decide whether to invest first in infrastructure, in management systems or in staff capacity. The State Ministry of Health and regulators can use them to design guidance and support that reflect conditions in public hospitals. Banks and payment providers can use them to understand which service failures most hinder uptake. For researchers, the study extends the HOT-fit model with an environmental dimension and tests it with PLS-SEM in a setting that has received little empirical attention.

LITERATURE REVIEW

Conceptual Review

Electronic Payment System Adoption

An electronic payment system is a digital arrangement through which payers and payees exchange value without physical cash, using channels such as POS terminals, mobile banking, online transfers and automated teller machines (Oyelami et al., 2020). Adoption refers to the extent to which individuals and organizations accept and routinely use such a system. It depends on user perceptions, such as usefulness, ease of use and trust, as well as on organizational readiness and facilitating conditions (Davis, 1989; Venkatesh et al., 2003). In the hospital context, Abugu et al. (2023) found that managers who perceived e-payment as useful and credible were more favourably disposed towards it, while technophobia lowered that disposition. In this study, adoption denotes the extent to which public hospitals in Jigawa State have accepted and use electronic channels for receiving and processing payments.

Technological Factors

Technological factors are the technical attributes and infrastructure that determine whether an electronic payment system can function reliably, including POS terminals and other hardware, stable internet connectivity, uninterrupted electricity and transaction security (Oliveira & Martins, 2011). Abugu et al. (2023) noted that concerns about electricity, internet service, network interruption and internet fraud persist despite the benefits of e-payment, and Adeniji et al. (2025) identified failed transactions and cybersecurity as challenges of digital payments in Nigerian health care. Where the technology is dependable and secure, users are more willing to rely on it (Shuaibu et al., 2023).

Organizational Factors

Organizational factors are the internal characteristics of the institution that shape adoption, such as top-management support, staff training, financial and technical resources, and clarity of internal policies and procedures (Yusof et al., 2008; Oliveira & Martins, 2011). Hospitals that provide leadership commitment, capacity building and clear operating procedures are better placed to integrate new systems, while under-resourced hospitals struggle to maintain and support them.

Environmental Factors

Environmental factors are the external conditions under which the hospital operates, including government regulation, the policy environment, the availability of banking and telecommunications services, and wider socio-economic conditions (Tornatzky & Fleischer, 1990). In Nigeria, the cashless policy and related digital payment policies form part of this environment (Adeniji et al., 2025). Unreliable power supply, weak connectivity and unclear regulatory guidance are external constraints that hospitals cannot easily control.

Human Factors

Human factors concern the people who use the system. Within the HOT-fit framework, the human dimension covers how widely and how well staff use the system and how satisfied they are with it, which in turn reflects their skills, training, expectations and attitudes towards acceptance or resistance (Yusof et al., 2008). For EPS, relevant attributes include digital literacy, confidence, resistance to change and fear of technology. Abugu et al. (2023) reported that technophobia was negatively related to managers' disposition towards e-payment.

Empirical Review and Hypothesis Development

Technological Factors and EPS Adoption

Studies of payment adoption in Nigeria consistently point to technology-related attributes. Oyelami et al. (2020) surveyed bank customers in Lagos State and found that convenience and security and safety were significant predictors of e-payment adoption. In a study of rural bank customers in Kano State, Abdurrahaman et al. (2021) extended the technology acceptance model and found that perceived usefulness strongly influenced eBanking adoption and that the quality of the internet connection was vital. In hospitals, Abugu et al. (2023) found that perceived usefulness and credibility, which relates to the robustness and security of platforms, predicted managerial disposition towards e-payment. These studies concern banking customers or managers rather than hospital staff in general, so the hospital-level effect of technology remains to be tested. The following hypothesis is therefore proposed:

H1: *Technological factors have a significant effect on the adoption of EPS in public hospitals in Jigawa State.*

Organizational Factors and EPS Adoption

Abugu et al. (2023) examined managerial staff in public tertiary hospitals and concluded that service providers must make platforms more secure and user-friendly, while hospital managers' attitudes shaped acceptance. Adeniji et al. (2025) reported that stakeholders in the Nigerian health sector found digital payment acceptable and that incentives for adoption included improved financial accountability and transparency, which are management concerns. The HOT-fit model itself holds that information systems succeed when the organizational environment, including structure, leadership and resources, fits the technology and its users (Yusof et al., 2008). Direct tests of organizational factors on EPS adoption in public hospitals are scarce, which motivates the second hypothesis:

H2: *Organizational factors have a significant effect on the adoption of EPS in public hospitals in Jigawa State.*

Environmental Factors and EPS Adoption

The policy and infrastructural environment can either support or constrain adoption. Adeniji et al. (2025) noted that the Nigerian government had introduced digital payment policies, including the cashless policy, but that challenges such as failed transactions, double payments and unfriendly bank policies persisted. Abugu et al. (2023) similarly observed that public hospitals had been slow to conform to the cashless policy. Evidence on the direction of the

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environmental effect is mixed, and it depends on whether the environment is experienced as enabling or restrictive. Hence:

H3: *Environmental factors have a significant effect on the adoption of EPS in public hospitals in Jigawa State*.

Human Factors and EPS Adoption

Individual attitudes and competencies are central to technology acceptance (Davis, 1989; Venkatesh et al., 2003). Abugu et al. (2023) found a negative correlation between technophobia and managerial disposition towards e-payment ($\rho = -0.50$), although perceptions of usefulness and credibility, rather than technophobia, remained significant in the multivariate model. Gholami et al. (2010) found that awareness, trust, effort expectancy and demographic variables affected Nigerians' intention to adopt e-payment, and Abdul-Hamid et al. (2019) showed that perceived risk reduced, and trust in providers increased, intention to use mobile money in Ghana. Because the effect of user attributes is not uniform across studies, the fourth hypothesis is stated as:

H4: *Human factors have a significant effect on the adoption of EPS in public hospitals in Jigawa State.*

Theoretical Framework

The study is anchored on the Human–Organization–Technology fit (HOT-fit) model, which Yusof et al. (2008) proposed to evaluate health information systems by extending the DeLone and McLean (2003) information systems success model. The model holds that success depends on the fit among human factors (system use and user satisfaction), organizational factors (structure and environment) and technological factors (system, information and service quality). Because the model was developed for health care, it suits payment systems embedded in hospital operations. Its organizational dimension, however, treats the external environment only indirectly. The study therefore draws on the technology–organization–environment (TOE) framework (Tornatzky & Fleischer, 1990), which treats the external context, including regulation and infrastructure, as a separate determinant of adoption, and which is widely used to explain technology adoption by firms and institutions (Oliveira & Martins, 2011).

Three individual-level theories support the human and technological dimensions. The technology acceptance model explains acceptance through perceived usefulness and perceived ease of use (Davis, 1989). The unified theory of acceptance and use of technology

adds performance expectancy, effort expectancy, social influence and facilitating conditions (Venkatesh et al., 2003). Diffusion of innovations theory emphasises relative advantage, compatibility, complexity, trialability and observability, along with communication channels within a social system (Rogers, 2003). Together these theories justify the four predictors used here: technological, organizational, human and environmental factors.

Research Framework

The research framework (Figure 1) adapts the HOT-fit model (Yusof et al., 2008) and adds environmental factors from the TOE framework (Tornatzky & Fleischer, 1990). It has four independent variables (technological, organizational, human and environmental factors) and one dependent variable, EPS adoption in public hospitals in Jigawa State.

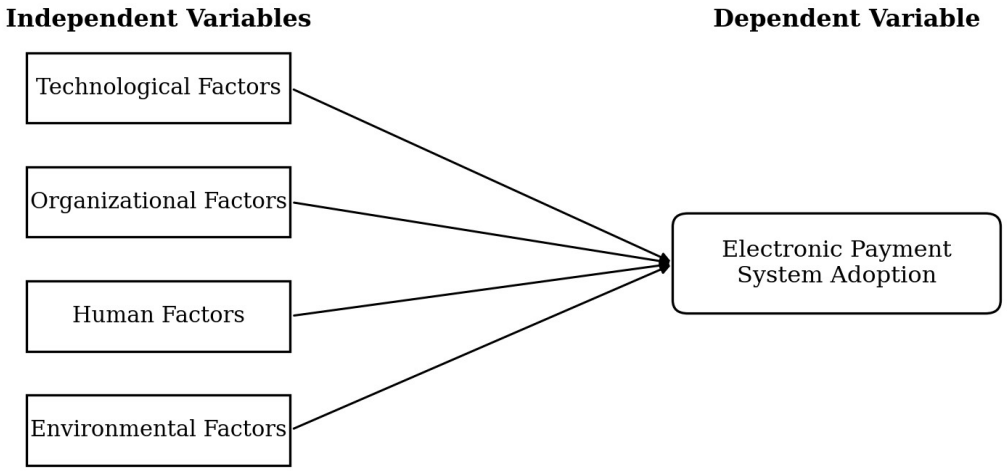


Figure 1: Research Framework

Source: Adapted from Yusof et al. (2008) and Tornatzky and Fleischer (1990).

MATERIALS AND METHODS

The study adopted a cross-sectional survey design, which collects data from respondents in different organizations at a single point in time and suits the quantitative testing of relationships among constructs. The population comprised staff of public hospitals in Jigawa State, namely the Federal Medical Centre Birnin Kudu, Rasheed Shekoni Specialist Hospital, ten general hospitals (Babura, Birnin Kudu, Birniwa, Dutse, Hadejia, Gumel, Ringim, Kazaure, Kafin Hausa and Jahun) and five cottage hospitals (Gwaram, Ringim, Birniwa, Bulangu and Kafin Hausa). Cottage hospitals were included because they represent grassroots health care, where infrastructure and digital literacy constraints are likely to be most severe.

The total population was approximately 3,750 staff as of 31 May 2026 (Jigawa State Ministry of Health, personal communication, May 31, 2026).

The sample size was determined with the Taro Yamane (1967) formula, $n = N / (1 + N(e)^2)$, where N is the population (3,750) and e is the margin of error (0.05). This gives $n = 3,750 / (1 + 3,750 \times 0.0025) = 3,750 / 10.375 \approx 361$. The sample is also adequate for PLS-SEM, whose minimum sample requirement depends on the number of predictors pointing at a construct (Hair et al., 2019), and here only four do.

The sample was allocated in proportion to the staff strength of each hospital (Table 1). Within hospitals, respondents were grouped by cadre (administrative staff, finance officers, ICT personnel), and simple random selection was then used within each group. Data were collected with a structured questionnaire built around the study objectives. Technological, organizational, environmental and human factors were each measured with five items, and EPS adoption with six items. Data were analysed with PLS-SEM in SmartPLS, following the two-stage procedure of assessing the measurement model and then the structural model (Hair et al., 2022). Significance was assessed by bootstrapping.

Table 1: Population and Sample Size

S/N	Hospital category	Hospital name	Population	Sample
1	Tertiary	Federal Medical Centre Birnin Kudu	441	42
2	Specialist	Rasheed Shekoni Specialist Hospital	265	26
3	General	Dutse	353	34
4	General	Hadejia	265	26
5	General	Kazaure	265	25
6	General	Kafin Hausa	265	25
7	General	Birnin Kudu	265	25
8	General	Gumel	221	21
9	General	Ringim	221	21
10	General	Babura	220	21
11	General	Jahun	220	21
12	General	Birniwa	176	17
13	Cottage	Gwaram Cottage Hospital	132	12
14	Cottage	Ringim Cottage Hospital	106	11
15	Cottage	Birniwa Cottage Hospital	88	9
16	Cottage	Bulangu Cottage Hospital	106	11
17	Cottage	Kafin Hausa Cottage Hospital	141	14
		Total	**3,750**	**361**

Source: Jigawa State Ministry of Health (2026); researcher's computation.

RESULTS AND DISCUSSIONS

SmartPLS was used to evaluate the measurement model and the structural model. The measurement model was assessed for indicator reliability, internal consistency reliability, convergent validity and discriminant validity, and the structural model for collinearity, the significance and size of path coefficients, explanatory power and model fit (Hair et al., 2019). Figure 2 presents the estimated model with outer loadings, path coefficients and R^2.

Response Rate

Out of the 361 questionnaires administered, 350 were returned (a return rate of 97.0%), and 346 were valid for analysis (95.8% of those administered). With 346 usable responses, the effective margin of error is approximately 5.1%, which is close to the 5% assumed in the sample size calculation. The usable sample far exceeds the requirements of the PLS-SEM model.

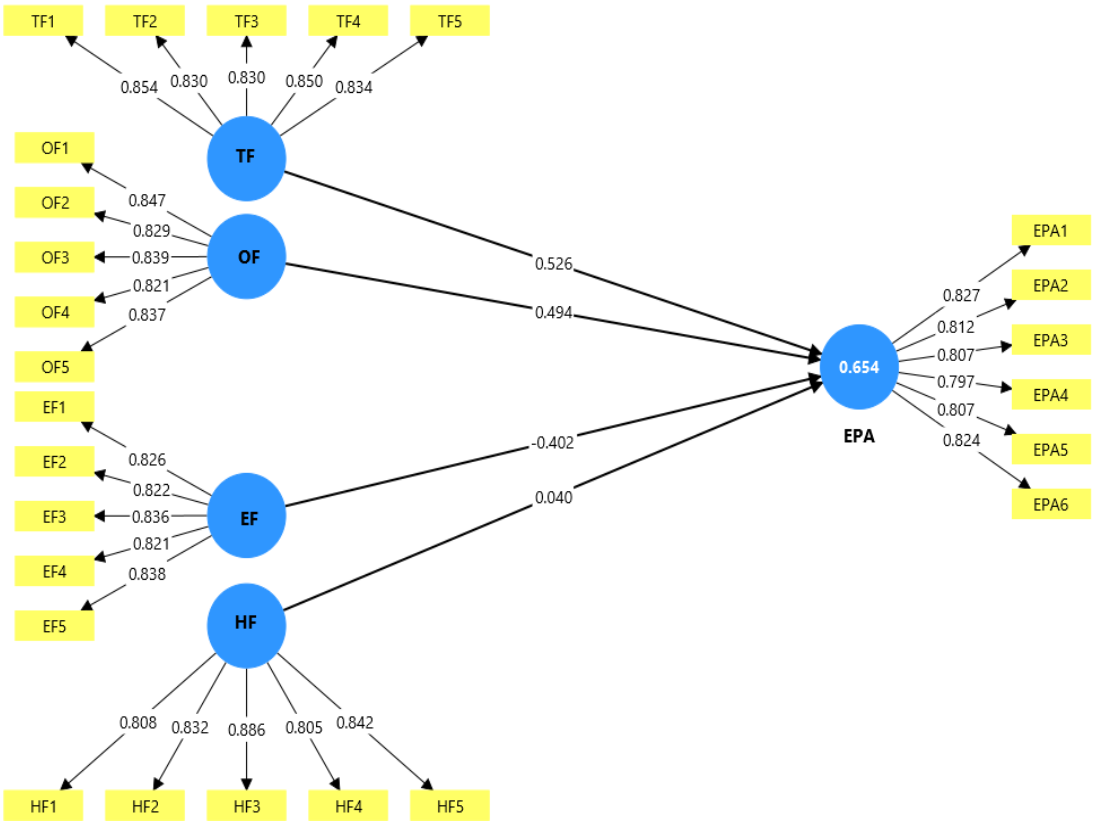


Figure 2: Estimated PLS-SEM Model (Outer Loadings, Path Coefficients and R^2)

Source: Researcher's computation using SmartPLS (2026).

Indicator Reliability

Indicator reliability is judged by the outer loadings, with values of 0.70 or higher regarded as acceptable (Hair et al., 2019). All 26 indicators loaded between 0.797 and 0.886 (Table 2), so no item needed to be removed. Each indicator therefore shares more than 50% of its variance

with its construct. The lowest loading was EPA4 (0.797) and the highest was HF3 (0.886). The bootstrapped t-values for all loadings were large (Figure 4), although those of the human factor items (5.860 to 6.584) were noticeably smaller than those of the other constructs (36.129 to 55.412), which indicates comparatively more variation in how respondents answered those items.

Internal Consistency Reliability

Internal consistency was assessed with Cronbach's alpha, composite reliability (rho_a) and composite reliability (rho_c), for which values between 0.70 and 0.95 are satisfactory (Hair et al., 2019). Table 2 shows that alpha ranged from 0.886 to 0.897, rho_a from 0.887 to 0.963 and rho_c from 0.916 to 0.923. Every construct therefore exceeds the 0.70 threshold. The rho_a of the human factor construct (0.963) is slightly above 0.95, which can signal item redundancy. Because its alpha (0.894) and rho_c (0.920) lie within the recommended range, this is not considered a serious problem.

Convergent Validity

Convergent validity was assessed with the average variance extracted (AVE), which should be at least 0.50 (Hair et al., 2019). The AVE values ranged from 0.660 (EPS adoption) to 0.705 (technological factors), so each construct explains more than 60% of the variance of its indicators.

Table 2: Indicator Loadings, Reliability and Convergent Validity of Latent Constructs

Latent construct	Item	Loading	Cronbach's α	CR (rho_a)	CR (rho_c)	AVE
EPS adoption (EPA)	EPA1	0.827	0.897	0.897	0.921	0.660
	EPA2	0.812				
	EPA3	0.807				
	EPA4	0.797				
	EPA5	0.807				
	EPA6	0.824				
Technological factors (TF)	TF1	0.854	0.895	0.897	0.923	0.705
	TF2	0.830				
	TF3	0.830				
	TF4	0.850				
	TF5	0.834				
Organizational factors (OF)	OF1	0.847	0.891	0.893	0.920	0.697
	OF2	0.829				
	OF3	0.839				

Latent construct	Item	Loading	Cronbach's α	CR (rho_a)	CR (rho_c)	AVE
	OF4	0.821				
	OF5	0.837				
Environmental factors (EF)	EF1	0.826	0.886	0.887	0.916	0.686
	EF2	0.822				
	EF3	0.836				
	EF4	0.821				
	EF5	0.838				
Human factors (HF)	HF1	0.808	0.894	0.963	0.920	0.697
	HF2	0.832				
	HF3	0.886				
	HF4	0.805				
	HF5	0.842				

Note: CR = composite reliability; AVE = average variance extracted.
Source: Researcher's computation using SmartPLS (2026).

Discriminant Validity

Discriminant validity shows that each construct is empirically distinct from the others. Two criteria were applied. The Fornell–Larcker criterion requires the square root of a construct's AVE to exceed its correlations with other constructs (Fornell & Larcker, 1981). In Table 3, the square roots of the AVE (0.812 to 0.840) are greater than all inter-construct correlations in their respective rows and columns. The largest correlation is that between technological factors and EPS adoption (0.518), which is well below 0.812 and 0.840.

Table 3: Discriminant Validity (Fornell–Larcker Criterion)

	EF	EPA	HF	OF	TF
EF	0.828				
EPA	−0.340	0.812			
HF	0.008	0.100	0.835		
OF	0.059	0.487	0.044	0.835	
TF	0.060	0.518	0.079	0.027	0.840

Note: Diagonal values (bold in the original output) are the square roots of the AVE. EF = environmental factors; EPA = EPS adoption; HF = human factors; OF = organizational factors; TF = technological factors.
Source: Researcher's computation using SmartPLS (2026).

Because the Fornell–Larcker criterion has been criticised for failing to detect discriminant validity problems in some situations, the heterotrait–monotrait (HTMT) ratio was also examined. Values below 0.85 indicate discriminant validity (Henseler et al., 2015). Table 4 shows that all HTMT ratios are below this threshold, with the highest being 0.576 (TF–EPA)

and the lowest 0.055 (EF–HF and HF–OF). The two criteria agree that the five constructs are distinct.

Table 4: Discriminant Validity (Heterotrait–Monotrait Ratio)

	EF	EPA	HF	OF	TF
EF					
EPA	0.381				
HF	0.055	0.104			
OF	0.074	0.543	0.055		
TF	0.074	0.576	0.088	0.063	

Source: Researcher's computation using SmartPLS (2026).

Correlation Matrix and Collinearity

Table 5 presents the correlations among the constructs and the inner variance inflation factors (VIF) for each predictor of EPS adoption. Technological factors (r = 0.518) and organizational factors (r = 0.487) correlate moderately and positively with adoption, environmental factors correlate negatively (r = −0.340), and human factors correlate only weakly (r = 0.100). The predictors are almost uncorrelated with one another ($|r| \leq 0.079$), which suggests that each captures a distinct aspect of the hospital setting. Consistent with this, the VIF values range from 1.006 to 1.010, far below the conservative cut-off of 3 (Hair et al., 2019). Multicollinearity is therefore not a concern, and the path coefficients can be interpreted without distortion.

Table 5: Correlation Matrix and Collinearity Statistics

	EF	EPA	HF	OF	TF	VIF (→ EPA)
EF	1.000					1.007
EPA	−0.340	1.000				
HF	0.008	0.100	1.000			1.008
OF	0.059	0.487	0.044	1.000		1.006
TF	0.060	0.518	0.079	0.027	1.000	1.010

Source: Researcher's computation using SmartPLS (2026).

Model Fit

Model fit was checked with the standardised root mean square residual (SRMR) and the normed fit index (NFI), as shown in Table 6. An SRMR below 0.08 indicates acceptable fit (Hu & Bentler, 1999; Henseler et al., 2014), and an NFI above 0.90 is conventionally regarded as acceptable (Bentler & Bonett, 1980). The estimated model's SRMR of 0.043 and NFI of 0.908 satisfy both criteria. The unweighted least squares distance ($d_ULS = 0.648$), the geodesic distance ($d_G = 0.246$) and chi-square (514.008) are identical for the saturated and

estimated models. Because the PLS chi-square has no established threshold, it is reported for completeness and not used for judgement.

Table 6: Model Fit Indices

Index	Saturated model	Estimated model
SRMR	0.043	0.043
d_ULS	0.648	0.648
d_G	0.246	0.246
Chi-square	514.008	514.008
NFI	0.908	0.908

Source: Researcher's computation using SmartPLS (2026).

Significance of Path Coefficients

The structural model was evaluated by bootstrapping, and the results are shown in Figures 2 to 4 and Table 7. All hypotheses were two-tailed, since each proposed that the factor has a significant effect without prespecifying its direction.

Table 7: Structural Estimates

Hypothesis	Relationship	β	Sample mean	SD	T-statistic	p-value	Decision
H1	TF → EPA	0.526	0.526	0.030	17.456	< .001	Supported
H2	OF → EPA	0.494	0.493	0.033	15.107	< .001	Supported
H3	EF → EPA	−0.402	−0.402	0.031	12.866	< .001	Supported (negative)
H4	HF → EPA	0.040	0.043	0.032	1.244	.214	Not supported

Note: p < .001. TF = technological factors; OF = organizational factors; EF = environmental factors; HF = human factors; EPA = EPS adoption.

Source: Researcher's computation using SmartPLS (2026).

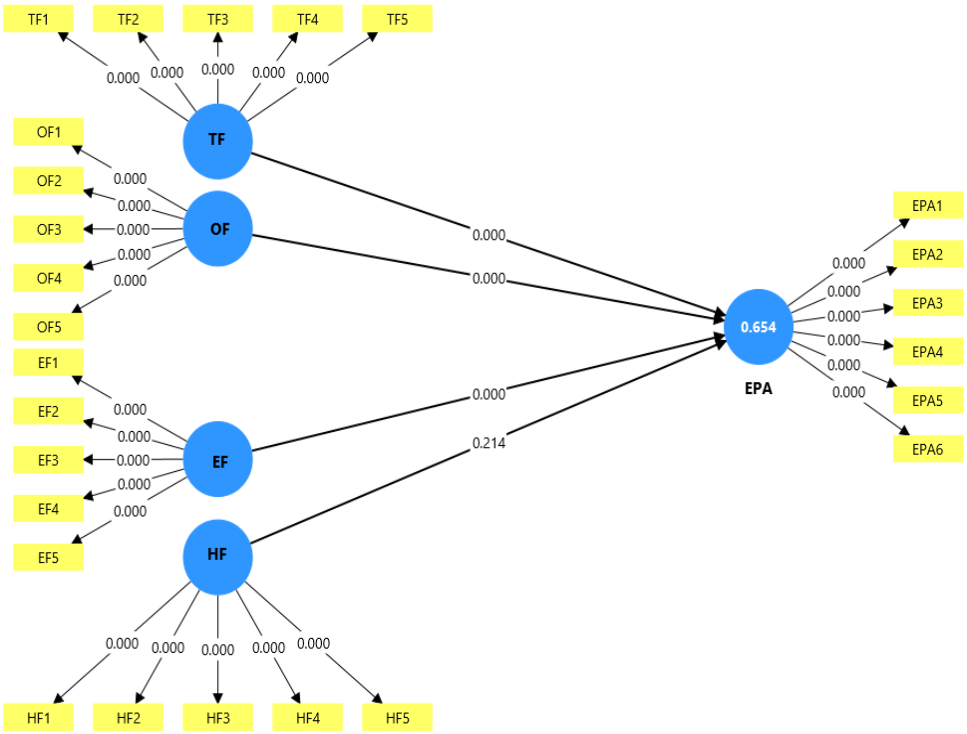


Figure 3: Bootstrapped p-values

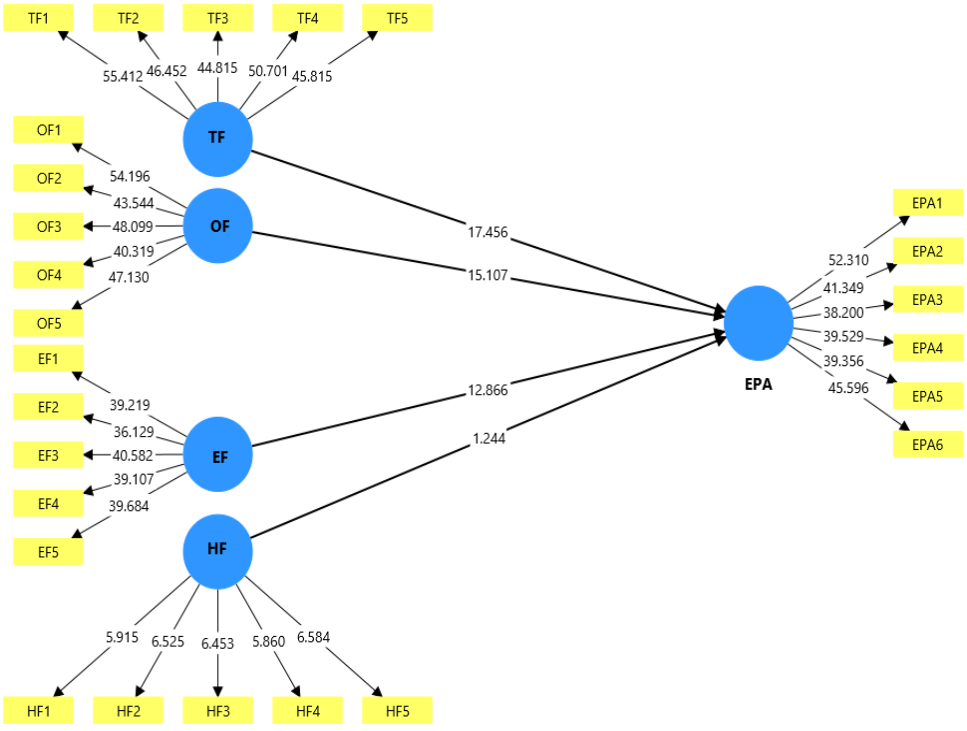


Figure 4: Bootstrapped t-values

Source: Researcher's computation using SmartPLS (2026).

Coefficient of Determination (R^2) and Effect Size (f^2)

The R^2 of EPS adoption is 0.654 (Figure 2), so technological, organizational, environmental and human factors jointly explain 65.4% of its variance, and factors outside the model explain

the remaining 34.6%. This is moderate, approaching substantial, explanatory power by common benchmarks (Chin, 1998; Hair et al., 2019).

Effect sizes (f^2) show how much R^2 falls when a predictor is removed; values of 0.02, 0.15 and 0.35 are regarded as small, medium and large (Cohen, 1988). They were computed from the correlations in Table 5, which reproduce the reported path coefficients and the R^2 of 0.654 (Table 8). Technological factors (f^2 = 0.789), organizational factors (f^2 = 0.702) and environmental factors (f^2 = 0.461) all have large effects, whereas human factors (f^2 = 0.005) have a negligible effect.

Table 8: Coefficient of Determination and Effect Sizes

Predictor	f^2	Effect size	R^2 (EPA)
Technological factors	0.789	Large	0.654
Organizational factors	0.702	Large	
Environmental factors	0.461	Large	
Human factors	0.005	Negligible	

Note: f^2 values were computed from the construct correlations in Table 5 and are not direct SmartPLS output.
Source: Researcher's computation.

Discussion of Findings

Four determinants of EPS adoption were examined. Technological and organizational factors had significant positive effects, environmental factors had a significant negative effect, and human factors had no significant effect. Each finding is discussed against earlier studies below.

Technological Factors and EPS Adoption

Technological factors had the strongest effect on adoption ($\beta = 0.526$, $t = 17.456$, $p < .001$), so H1 is supported. Hospitals whose staff view the available hardware, network connectivity, power supply and transaction security as dependable are more likely to have adopted electronic payments. This agrees with Oyelami et al. (2020), who found convenience and security and safety to be significant predictors of e-payment adoption among bank customers in Lagos, and with Abdurrahaman et al. (2021), who highlighted the importance of internet connection quality for rural bank customers. It is also consistent with Abugu et al. (2023), whose hospital managers were more disposed towards e-payment when they perceived platforms as useful and credible, and with the concern of Adeniji et al. (2025) that failed transactions and cybersecurity weaknesses undermine digital payments in Nigerian health care. A plausible reason for the strength of this effect is that hospital payments are time-sensitive. A failed or slow transaction at a pay point delays treatment, so staff quickly learn

whether the technology can be trusted. The implication is that hardware, connectivity and security should be addressed before wider roll-out.

Organizational Factors and EPS Adoption

Organizational factors also had a significant positive effect ($\beta = 0.494$, $t = 15.107$, $p < .001$), so H2 is supported. Hospitals with supportive management, trained staff and clear internal procedures are more likely to adopt EPS. The result accords with the HOT-fit proposition that systems succeed when the organization provides the structure and resources that fit the technology and its users (Yusof et al., 2008). It is also in line with Abugu et al. (2023), who found that the attitudes of hospital managers shaped acceptance of e-payment, and with Adeniji et al. (2025), who noted that improved financial accountability and transparency motivated the digitisation of payments in the health sector. In public hospitals, financial decisions pass through bureaucratic channels, so adoption depends heavily on management commitment, funding and training for staff to use the system. The effect size ($f^2 = 0.702$) shows that organizational readiness is almost as important as the technology itself.

Environmental Factors and EPS Adoption

Environmental factors had a significant but negative effect ($\beta = -0.402$, $t = 12.866$, $p < .001$), so H3 is supported in terms of significance, although the direction differs from what a purely enabling environment would produce. The negative sign means that hospitals whose respondents report stronger external pressures and constraints, such as unreliable electricity, poor connectivity, unclear regulatory guidance and weak bank support, show lower adoption. This agrees with the evidence that, despite the cashless policy, public hospitals have been slow to conform (Abugu et al., 2023) and that failed transactions and unfriendly bank policies persist in the health sector (Adeniji et al., 2025). Fraud in electronic banking, documented by Ololade et al. (2020), may also contribute to cautious attitudes. The interpretation of the sign depends on how the environmental items are worded: if they describe external obstacles, agreement with them naturally reduces adoption. The negative effect is nonetheless substantial ($f^2 = 0.461$) and indicates that the external environment is currently a barrier rather than an enabler of EPS in Jigawa State public hospitals.

Human Factors and EPS Adoption

Human factors had no significant effect on adoption ($\beta = 0.040$, $t = 1.244$, $p = .214$; $f^2 = 0.005$), so H4 is not supported. This differs from Abugu et al. (2023), who found technophobia to be negatively related to managerial disposition, and from Gholami et al. (2010), who reported that awareness, trust and demographic variables influenced intention to adopt e-payment. It is consistent, however, with the multivariate result of Abugu et al. (2023), where technophobia

did not remain a significant predictor once other perceptions were controlled. Several explanations are plausible but were not tested here. Electronic payment in public hospitals is largely provided through banks and imposed by institutional and policy arrangements, so individual staff attitudes may matter less than the infrastructure and organizational support. Staff skills may also be relatively uniform in the sample. In addition, the human factor items had comparatively lower bootstrapped t-values (Figure 4), indicating more variation in responses. Training should still be provided, since it is a management responsibility captured in the organizational dimension.

CONCLUSION AND RECOMMENDATIONS

Conclusion

This study set out to identify the factors that determine the adoption of electronic payment systems in public hospitals in Jigawa State. The measurement model met the required standards of reliability and validity, and the structural model fitted well and explained 65.4% of the variance in adoption. Technological and organizational factors significantly increase adoption, environmental factors significantly reduce it, and human factors have no significant effect. Hospital payment systems are therefore shaped mainly by the quality of technology, the support given by management and the external conditions under which hospitals work, and less by the attributes of individual staff.

Recommendations

In line with the conclusion of this study, the study recommends the following:

(i) Hospital management and the State Ministry of Health should invest in dependable POS terminals, stable internet connectivity and backup power at payment points, giving priority to general and cottage hospitals, and should work with banks on transaction security and fast resolution of failed transactions.

(ii) Hospital management should demonstrate visible commitment to EPS by setting clear operating procedures, assigning responsibility for payment platforms and funding regular staff training.

(iii) Policymakers and regulators should issue clear guidance on the use of electronic payments in public hospitals, including accountability and audit requirements, and should address the infrastructure and banking-service gaps that currently act as barriers.

(iv) Banks and payment providers should improve platform security and reliability and provide on-site support to hospitals.

Suggestions for Further Research

The study was limited to public hospitals in one state and relied on self-reported perceptions at one point in time, so the findings may not generalise to other states or to private hospitals, and causal direction cannot be established. Patients, who also determine whether electronic channels are used, were not surveyed. Future studies could extend the research to other states, compare public and private hospitals, include patients' perspectives, use longitudinal designs, and add variables such as trust, perceived risk and cost to explain the 34.6% of variance left unexplained.

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