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Evaluating the Adoption of Expert Systems, Inventory Management Practices and Digital Readiness in Nigerian Pharmaceutical Retail Organizations

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ABSTRACT

Pharmaceutical inventory management is vital for ensuring medicine availability, patient safety, and operational sustainability. However, pharmaceutical retail organizations in developing economies continue to experience persistent stock-outs, drug expiries, and supplier delivery delays due to reliance on manual and semi-digital inventory systems. Despite the growing potential of Expert Systems (ES), empirical evidence on organizational readiness and behavioural intention toward ES adoption remains limited. This study investigates inventory management challenges and evaluates the organizational, technological, and behavioural factors influencing Expert System adoption in Nigerian pharmaceutical retail organizations. The novelty of this study lies in the development and empirically the validation of an integrated Expert System framework that combines technology adoption determinants with intelligent inventory optimization. Grounded in the Technology Acceptance Model (TAM), Technology–Organization–Environment (TOE) framework, and Unified Theory of Acceptance and Use of Technology (UTAUT), a cross-sectional survey of 293 pharmacy professionals was analyzed using descriptive and inferential statistics. Findings reveal high levels of stock-outs (Mean = 3.70), recurring drug expiry (Mean = 3.59), and supplier delivery delays (Mean = 3.77), indicating persistent operational inefficiencies. Conversely, strong digital readiness (Mean = 3.65), organizational willingness (Mean = 4.00), perceived decision accuracy improvement (Mean = 4.15), and behavioural intention toward ES adoption (Mean = 4.30) indicate a favourable implementation environment. The proposed framework integrates automated stock alerts, machine learning–based demand forecasting, and rule-based decision support to improve medicine availability, reduce inventory waste, enhance operational efficiency, and advance technology adoption theories within pharmaceutical retail supply chains in developing economies.

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INTRODUCTION

Pharmaceutical retail inventory management differs fundamentally from conventional retail operations due to regulatory requirements, therapeutic criticality, batch traceability, and expiry sensitivity. Inventory inefficiencies directly impact patient health outcomes and healthcare system resilience. Recent studies have emphasized that weaknesses in pharmaceutical supply chains, including inaccurate inventory information, demand uncertainty, stock-outs, overstocking, and product expiry, can adversely affect medicine availability and healthcare-system resilience (World Health Organization [WHO], 2022; OECD, 2023).

Nigeria faces similar challenges within its pharmaceutical supply chain. The increasing emphasis on digital health and health-information systems has highlighted the need for reliable, timely, and integrated data to support healthcare decision-making. Nevertheless, limitations in digital infrastructure, interoperability, human capacity, and organizational preparedness can constrain the effective adoption and utilization of digital technologies within healthcare and pharmaceutical operations (Federal Ministry of Health, 2022; WHO, 2021).

In healthcare, AI-based decision-support technologies have demonstrated potential for augmenting professional decision-making, although their effectiveness depends on data quality, explainability, integration with existing workflows, and user acceptance (Yu et al., 2021; WHO, 2021). However, successful deployment requires more than technical capability. Organizational readiness, user trust, perceived usefulness, and environmental constraints critically influence adoption outcomes. Contemporary research on AI adoption emphasizes that organizational and human factors, including trust, transparency, explainability, skills, governance, and perceived value, can significantly influence the acceptance and effective use of AI-enabled systems (Glikson & Woolley, 2020; Dwivedi et al., 2021; Jöhnk et al., 2021). This study addresses a significant research gap by empirically examining the intersection of operational inventory challenges and technology adoption dynamics in pharmaceutical retail organizations.

Literature Review

Pharmaceutical Inventory Management Challenges

Pharmaceutical inventory systems must balance availability with wastage control. Research consistently reports that manual systems increase vulnerability to stock-outs and expiry losses (World Health Organization [WHO], 2021; OECD, 2023; Mohamed & El-Saber, 2023). Poor demand forecasting and weak supply chain visibility contribute to inefficiencies, particularly in resource-constrained environments (Sharma, 2021; Hassan et al., 2024). Inventory management in pharmaceutical contexts involves ensuring the right medicines are available, in the right quantities, at the right time, while minimizing wastage and ensuring regulatory compliance (Khatib et al., 2024; Tan et al., 2024). Unlike general retail, pharmaceutical inventory systems must account for expiry dates, batch traceability, and therapeutic criticality (World Health Organization, 2022; Mohamed & El-Saber, 2023; Khatib et al., 2024). Consequently, there is increasing interest in integrating intelligent inventory systems, predictive analytics, artificial intelligence, and decision-support technologies to improve forecasting accuracy, optimize stock levels, and reduce medicine wastage across pharmaceutical supply chains (Secinaro et al., 2021; Tan et al., 2024).

Studies consistently report that manual inventory systems are associated with higher rates of stock-outs and expiries (Mustaffa & Potter, 2009). Kelle et al. (2012) argue that poor visibility across supply chains limits proactive replenishment and increases vulnerability to supplier delays. These challenges are exacerbated in environments with limited infrastructure and fragmented distribution networks.

Expert Systems and Intelligent Decision Support

In inventory management contexts, Expert Systems and intelligent decision-support technologies can support automated reorder alerts, demand forecasting, inventory-level optimization, expiry monitoring, procurement planning, and supplier-performance analysis by combining domain knowledge with historical and real-time operational data (Secinaro et al., 2021; Dwivedi et al., 2021; Jöhnk et al., 2021). The application of artificial intelligence and machine-learning techniques further enables inventory systems to identify demand patterns, improve forecasting accuracy, detect anomalies, and generate adaptive recommendations from continuously updated data (Yu et al., 2021; Kourentzes et al., 2022; Toorajipour et al., 2021). In pharmaceutical and healthcare supply chains, these capabilities are particularly relevant because demand uncertainty, stock-out risks, product expiry, supply disruptions, and the need for timely replenishment require more dynamic and data-driven approaches to inventory decision-making (WHO, 2021; OECD, 2023).

Expert Systems apply encoded domain knowledge, inference mechanisms, and computational reasoning to support decision-making in complex and knowledge-intensive environments. Contemporary intelligent decision-support systems increasingly combine these knowledge-based approaches with artificial intelligence and machine-learning techniques to enhance analytical capabilities, adaptability, and decision support (Dwivedi et al., 2021; Secinaro et al., 2021; Yu et al., 2021).

In pharmaceutical inventory management, such systems can integrate historical demand data, supplier performance, and consumption trends to generate actionable insights. Recent advancements incorporating machine learning further enhance forecasting accuracy and adaptability (Choi, Wallace, & Wang, 2018).

Empirical studies suggest that intelligent inventory systems reduce stock-outs, improve service levels, and enhance cost efficiency. However, technological effectiveness alone does not guarantee adoption or sustained use.

Theoretical Foundations

This study integrates three dominant technology adoption models, Technology Acceptance Model (TAM), Technology–Organization–Environment (TOE) Framework and Unified Theory of Acceptance and Use of Technology (UTAUT)

The integration of these frameworks provides a comprehensive lens for analyzing Expert System adoption in pharmaceutical retail contexts.

Technology Acceptance Model (TAM)

The Technology Acceptance Model (TAM) is theoretically rooted in the Theory of Reasoned Action (TRA) developed by Fishbein and Ajzen and was subsequently formulated by Davis as a model for explaining individuals' acceptance and use of information technology. Contemporary research continues to recognize TAM as one of the most influential theoretical models for explaining technology acceptance and users' behavioural intentions toward technological systems (Dwivedi et al., 2021; Marangunić & Granić, 2021). The model emphasizes the importance of Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) as fundamental determinants of users' attitudes and intentions to use a technology. Perceived usefulness reflects the extent to which an individual believes that using a particular system will enhance job or task performance, whereas perceived ease of use refers to the degree to which the individual expects the system to be free of effort (Marangunić & Granić, 2021; Scherer, Siddiq, & Tondeur, 2022). Recent studies have continued to apply and extend TAM to explain technology adoption across healthcare, artificial intelligence, and other digitally enabled organizational environments, demonstrating the continuing relevance of perceived usefulness, ease of use, trust, and behavioural intention in technology-adoption decisions (Secinaro et al., 2021; Dwivedi et al., 2021; Yu et al., 2021). Figure 1 presents the Technology Acceptance Model (TAM) and illustrates the relationships among external variables, perceived usefulness, perceived ease of use, attitude toward using, behavioural intention to use, and actual system use.

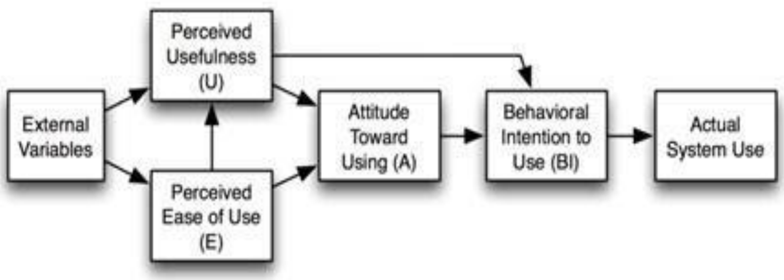

Figure 1: Technology Acceptance Model
Source: Davis 1986, Technology Acceptance Model Propped by Fred Davis

As illustrated in Figure 1, external variables can influence both perceived usefulness and perceived ease of use. In the context of this study, external variables may include organizational readiness, availability of ICT infrastructure, management support, user training, system quality, data quality, and regulatory requirements. Perceived ease of use may influence perceived usefulness because a system that is easy to understand and operate is more likely to be perceived as useful by its intended users.

Technology–Organization–Environment (TOE) Framework

The TOE framework emphasizes that adoption is influenced by technological characteristics, organizational readiness, and environmental conditions (Tornatzky & Fleischer, 1990). In developing economies, environmental factors such as infrastructure reliability, regulatory frameworks, and financial capacity play a decisive role in technology adoption (Oliveira & Martins, 2011). Figure 2 presents the Technology–Organization–Environment (TOE) framework, which explains technological innovation decision-making as a function of technological, organizational, and external environmental factors. The framework is relevant to this study because the adoption of an intelligent pharmaceutical inventory-management system is likely to depend not only on the capabilities of the technology but also on organizational readiness and external environmental conditions, including regulatory requirements, industry characteristics, and technological infrastructure.

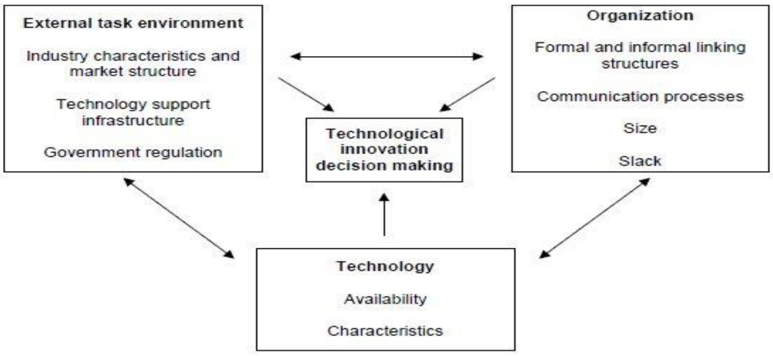

Figure 2: Technology-Organization-Environmental (TOE) framework Model
Source: Tornatzky & Fleischer, (1990). The Processes of Technological Innovation

Technology-Organization-Environmental (TOE) framework introduced by Tornatzky and Fleischer (1990) as shown in fig. 2, is a popular model for investigating the adoption of latest technologies in an organization. It classifies the factors that influence an organization to adopt new technology into three groups: technology, organization, and environment. The technological context refers to the existing as well as new technologies relevant to the firm. These factors play a significant role in the firm's adoption decision as it determines the ability of the firm to benefit from e-business initiative. The organizational context represents the internal factors in an organization, influencing an innovation adoption and implementation. Organizational context refers to descriptive measures about the organization such as scope, size, organization structure, financial support, managerial beliefs and top management support. The environmental context is the arena surrounding a firm, consists of its industry, technology support infrastructure and government regulation (Tornatzky and Fleischer 1990).

Ali, Shrestha, Osmanaj, and Muhammed (2020) identify the Technology–Organization–Environment (TOE) framework as an appropriate theoretical perspective for explaining technology adoption within organizational contexts. Similarly, studies by Muafi, Religia, and Ramawati (2024) and Religia, Surachman, Rohman, and Indrawati (2021) demonstrate that the TOE framework can provide substantial predictive power when examining organizational decisions concerning the adoption of information technology innovations. The technological dimension has also been recognized as an important determinant of technology adoption, with previous studies highlighting its influence on organizations' decisions to adopt emerging technologies (Abdurrahman, Gustomo, & Prasetio, 2024; Kumar & Shankar, 2024). In particular, small and medium-sized enterprises (SMEs) are more likely to adopt information technologies when they perceive them as beneficial, useful, and compatible with their organizational values and practices (Religia et al., 2021).

The organizational dimension is equally important in explaining technology adoption. Bening, Dachyar, Pratama, Park, and Chang (2023) and Bhatiasevi and Naglis (2018) report that organizational factors are among the most frequently examined determinants of innovation adoption in SMEs. Further empirical evidence confirms that organizational characteristics and internal capabilities can significantly influence technology-adoption decisions (Ninčević Pašalić & Ćukušić, 2024; Qalati, Li, Ahmed, Mirani, & Khan, 2021). In addition, Filipe, Ruivo, and Oliveira (2023) and Religia (2022) emphasize the importance of the environmental context in shaping organizations' decisions to adopt information technologies. Changes in the external business environment can increase the complexity of innovation and intensify competitive pressures, thereby encouraging SMEs to pursue technological innovation as a means of maintaining competitiveness and contributing to economic development (Barkley & Jokonya, 2024).

Despite the broad application and empirical support for the TOE framework, some studies have raised concerns about the consistency and predictive relevance of its individual dimensions. Kam and Tham (2022), for example, argue that technological factors do not invariably constitute the dominant influence on technology-adoption decisions. Similarly, Tiwari, Marak, Paul, and Deshpande (2023) question whether organizational-context indicators consistently provide effective predictions of technology adoption. Further evidence from Himawan, Djuwaini, and

Darmawan Putra (2024) indicates that technological and organizational readiness among SMEs may not have a statistically significant effect on innovation-adoption decisions. These contrasting findings suggest that the explanatory power of the TOE framework may vary according to the technological context, organizational characteristics, industry, and environmental conditions under investigation. Consequently, the framework should be applied with careful consideration of context-specific factors, particularly when examining the adoption of intelligent decision-support and inventory-management technologies in pharmaceutical retail organizations.

Unified Theory of Acceptance and Use of Technology (UTAUT)

The Unified Theory of Acceptance and Use of Technology (UTAUT) integrates multiple adoption theories and identifies performance expectancy, effort expectancy, social influence, and facilitating conditions as core determinants of system use (Venkatesh et al., 2003; Han & Han, 2022**)**. Healthcare studies continue to confirm that facilitating conditions, particularly organizational infrastructure and technical support frameworks, significantly dictate or moderate digital health adoption outcomes **(**Li & Zhang, 2025**;** Sharifian & Nematollahi, 2023**)**. The continuing quest to ensure user acceptance of technology is a persistent management challenge (Schwarz and Chin, 2007). Because this pursuit has occupied the minds of researchers for decades, technology adoption and diffusion research is now widely considered to be among the most mature and thoroughly explored areas of exploration in information systems **(**Dwivedi et al., 2021**;** Sousa & Ramos, 2024**).** This situation, in turn, has challenged researchers, as they are often forced to pick and choose characteristics across a wide variety of often competing models and theories. In response to this challenge, and in order to harmonize the literature associated with acceptance of new technology, Venkatesh et al. (2003) developed a unified model that brings together alternative views on user and innovation acceptance – The unified theory of acceptance and use of technology (UTAUT).

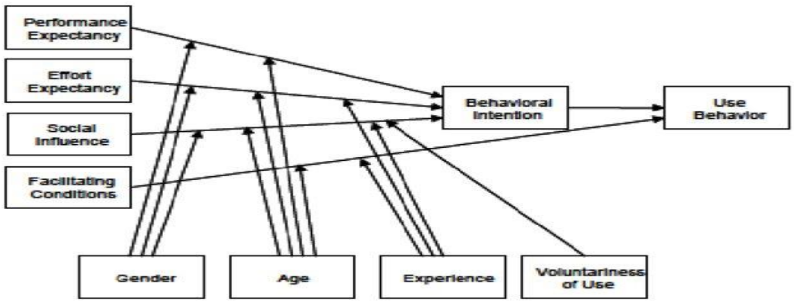

Figure 3: Unified Theory of Acceptance and Use of Technology (UTAUT) Model
Source: Venkatesh, et al (2003). User acceptance of information technology. pp. 447

The UTAUT (Figure 3) suggests that four core constructs (performance expectancy, effort expectancy, social influence and facilitating conditions) are direct determinants of behavioural intention and ultimately behaviour, and that these constructs are in turn moderated by gender, age, experience, and voluntariness of use (Venkatesh et al., 2003).

MATERIALS AND METHODS

Research Design

A cross-sectional survey design was adopted to collect data from pharmaceutical professionals actively involved in inventory decision-making.

Sample

A total of 293 valid responses were obtained through purposive sampling from pharmaceutical retail organizations in Edo North Senatorial District, Edo State, Nigeria. The respondents comprised personnel from community pharmacies (59%)**,** hospital pharmacies (19.8%), and wholesale/distribution outlets (17.1%).

Instrument

The structured questionnaire was designed to measured inventory challenges, digital readiness, perceived usefulness, trust in system recommendations and behavioural intention to use Expert Systems. The questionnaire items were measured using a five-point Likert scale ranging from 1 = Strongly Disagree to 5 = Strongly Agree. Reliability analysis yielded Cronbach's alpha values exceeding 0.70 across the study constructs, indicating acceptable internal consistency. The questionnaires were administered electronically through online platforms and social media channels to reach eligible respondents in pharmaceutical retail organizations.

Data Analysis

Descriptive statistics, correlation analysis, and regression modeling were employed. Thematic analysis was used for open-ended responses.

RESULTS AND DISCUSSION

Operational Challenges

Table 1 shows results for operational challenges variables and their corresponding means and their interpretations as also seen in figures 4, 5 and 6.

Table 1: Results for Operational Challenges

Variable	Mean	Interpretation
Stock –outs	3.70	High prevalence
Drug expiry	3.59	Recurring inefficiency
Supplier delays	3.77	Major supply chain constraint

The coexistence of stock-outs and expiry reveals structural imbalance in procurement and forecasting processes.

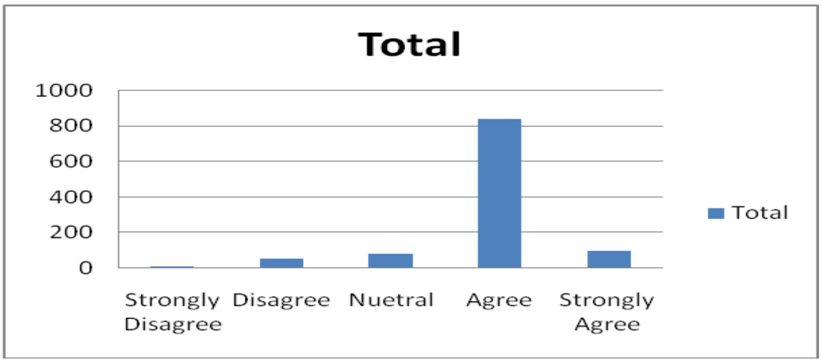

Figure 4: Stock-Outs of Essential Medicines Responses

From figure 4, the high frequency with the mean value of 3.70 of stock-outs directly increases the perceived need for intelligent inventory management systems. Within the Technology Acceptance Model (TAM), operational inefficiencies increase perceived usefulness, which significantly drives technology adoption behaviour.

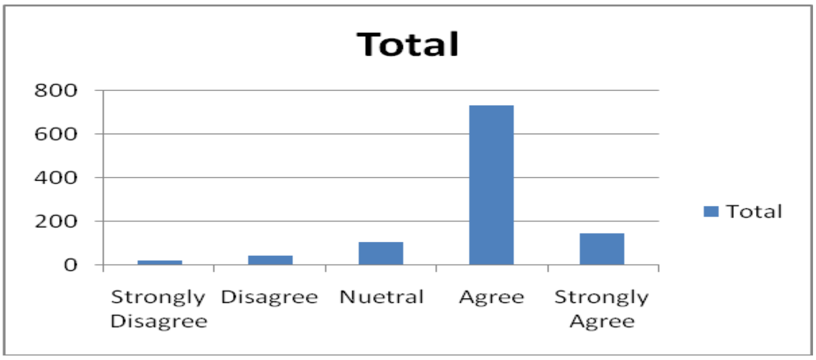

Figure 5: Drug Expiry and Inventory Wastage Responses

From figure 5, the descriptive statistical analysis demonstrates that expired drugs constitute a recurring and significant problem in pharmaceutical retail inventory management. The relatively high mean score of 3.59, negative skewness, and moderate variability collectively confirm widespread agreement among pharmacy professionals regarding the persistence of drug expiry challenges.

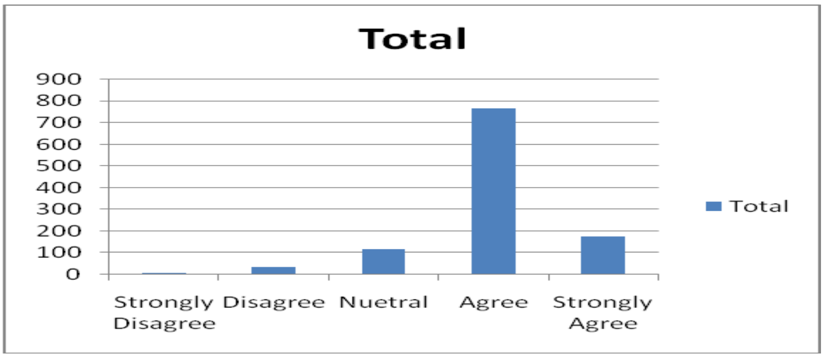

Figure 6: Supplier Delivery Delays

When compared with stock-out and drug expiry findings, supplier delivery delays appear to represent a major root cause of pharmaceutical inventory inefficiencies. The combined findings suggest a systemic inventory management problem characterized by poor supply chain coordination, inefficient procurement forecasting, limited real-time inventory monitoring etc.

Digital Readiness

Table 2 shows results for Digital Readiness variables and their corresponding means.

Table 2: Results for Digital Readiness

Variable	Mean
ICT literacy	3.65
Organizational willingness	4.00

These results indicate strong readiness for digital transformation. Policymakers and regulators should leverage this high willingness by creating supportive regulatory frameworks and incentives for healthcare technology adoption.
The descriptive statistical analysis reveals a strong and consistent willingness among pharmaceutical retail organizations to adopt new technologies. The high mean score, low dispersion, and strong negative skewness collectively demonstrate widespread acceptance and readiness for innovation.
These findings provide strong empirical justification for the implementation of Expert Systems and intelligent inventory management technologies, confirming that organizational attitude is a facilitating factor rather than a barrier to digital transformation in pharmaceutical retail operations.
Such willingness provides a strong institutional foundation for implementing Expert Systems, provided that infrastructural and financial barriers are addressed.

Perception of Expert Systems
Table 3 shows results for Perception of Expert Systems constructs and their corresponding means.

Table 3: Mean Results for Perception of Expert Systems Constructs

Construct	Mean
Decision accuracy improvement	4.15
Automated stock alerts	4.04
ML forecasting	3.99
Trust in system recommendations	3.91
Behavioral intention to use	4.30

In table 3, high behavioural intention confirms strong adoption potential. The descriptive statistical analysis demonstrates a strong and consistent intention among pharmacy professionals to use an Expert System if implemented. The high mean score, low variability, and negatively skewed distribution collectively indicate widespread readiness and acceptance of intelligent inventory management technologies.
Table 4 represents the correlation analysis of the digital readiness and organizational capacity, which demonstrates strong positive correlations and reveals a cohesive digital readiness ecosystem.

Table 4: Correlations of Digital Readiness and Organizational Capacity

		C1.	C2.	C3.	C4.	C5.
C1. I am comfortable using digital tools for pharmacy operations.	Correlation Coefficient	1.000	.349**	.344**	.366**	.266**
	Sig. (2-tailed)	-	.000	.000	.000	.000
	N	293	293	293	293	293
C2. Internet connectivity is stable enough for digital systems.	Correlation Coefficient	.349**	1.000	.510**	.368**	.365**
	Sig. (2-tailed)	.000	-	.000	.000	.000
	N	293	293	293	293	293
C3. Power supply supports the use of computer-based systems.	Correlation Coefficient	.344**	.510**	1.000	.367**	.424**
	Sig. (2-tailed)	.000	.000	-	.000	.000
	N	293	293	293	293	293
C4. Staff have adequate ICT literacy to use advanced systems.	Correlation Coefficient	.366*	.368**	.367**	1.000	.405**
	Sig. (2-tailed)	.000	.000	.000	-	.000
	N	293	293	293	293	293
C5. Our pharmacy is willing to adopt new technologies.	Correlation Coefficient	.266**	.365**	.424**	.405**	1.000
	Sig. (2-tailed)	.000	.000	.000	.000	-
	N	293	293	293	293	293

From table 4, all digital readiness variables demonstrate moderate to strong positive correlations, including comfort using digital tools (C1) significantly correlates with Internet stability (C2), Power supply reliability (C3), ICT literacy (C4) and Willingness to adopt new technologies (C5), internet connectivity (C2) and power supply (C3) show a strong association ($\rho = 0.510$, $p < 0.01$), ICT literacy (C4) significantly correlates with Willingness to adopt technology (C5) ($\rho = 0.405$, $p < 0.01$). The results reveal a cohesive digital readiness ecosystem. Pharmacies that possess stable infrastructure, digitally skilled staff, and reliable connectivity are significantly more inclined toward adopting new technologies. This suggests that organizational readiness is cumulative: deficiencies in infrastructure or staff capacity can undermine adoption, even when attitudes toward technology are positive. The findings reinforce the argument that technology adoption is contingent not only on perceived benefits but also on enabling conditions.
Also, the strong relationships between perceived usefulness (D1–D3), trust (D4), and intention to use (D5) empirically validate TAM's causal chain as shown in table 5.

Table 5: Correlations of Perception and acceptance of Expert System

			D1.	D2.	D3.	D4..	D5.
Spearman's rho	D1. An Expert System would improve accuracy of decision-making.	Correlation Coefficient	1.000	.385**	.542**	.184**	.401**
		Sig. (2-tailed)	.	.000	.000	.002	.000
		N	293	293	293	293	293
	D2. Automated stock alerts would reduce stock-outs.	Correlation Coefficient	.385**	1.000	.326**	.394**	.229**
		Sig. (2-tailed)	.000	.	.000	.000	.000
		N	293	293	293	293	293

			D1.	D2.	D3.	D4..	D5.
	D3. Machine Learning - powered forecasting would improve procurement planning.	Correlation Coefficient	.542**	.326**	1.000	.260**	.348**
		Sig. (2-tailed)	.000	.000	.	.000	.000
		N	293	293	293	293	293
	D4. I trust system-generated recommendations.	Correlation Coefficient	.184**	.394**	.260**	1.000	.348**
		Sig. (2-tailed)	.002	.000	.000	.	.000
		N	293	293	293	293	293
	D5. I would use an Expert System if implemented.	Correlation Coefficient	.401**	.229**	.348**	.348**	1.000
		Sig. (2-tailed)	.000	.000	.000	.000	.
		N	293	293	293	293	293

**. Correlation is significant at the 0.01 level (2-tailed).

Significant correlations among C-variables align with facilitating conditions and performance expectancy, reinforcing their influence on behavioral intention, the Unified Theory of Acceptance and Use of Technology (UTAUT). The results demonstrate that technological (system capability), organizational (ICT literacy), and environmental (infrastructure) factors jointly shape adoption outcomes which validates Technology–Organization–Environment (TOE) Framework.

Discussion

The correlation analysis reveals strong and statistically significant positive relationships between the key predictor variables and adoption intention, providing robust preliminary evidence of theoretical alignment with the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT).

On Perceived Usefulness and Adoption Intention ($r > 0.60$, $p < 0.01$), the correlation coefficient exceeding 0.60 indicates a strong positive relationship between perceived usefulness and intention to adopt the Expert System. This suggests that as pharmacy professionals increasingly believe that the system will enhance decision accuracy, reduce stock-outs, and improve procurement planning, their willingness to adopt it rises substantially.

Statistically, a coefficient above 0.60 in behavioral research reflects a practically meaningful association. The significance level ($p < 0.01$) confirms that this relationship is not due to random variation but represents a consistent pattern within the sample. Conceptually, this finding strongly supports TAM, which posits perceived usefulness as the most powerful determinant of technology acceptance.

On Trust and Adoption Intention ($r > 0.55$, $p < 0.01$), the positive correlation above 0.55 demonstrates that trust in system-generated recommendations significantly influences adoption intention as seen in table 5. In AI-enabled systems, trust reduces uncertainty and perceived risk. Pharmacy professionals must rely on automated stock alerts and forecasting outputs; thus, confidence in system reliability is critical.

This finding reinforces UTAUT's emphasis on performance expectancy and facilitating conditions, highlighting that technical capability alone is insufficient—users must trust the outputs for adoption to occur.

On Digital Readiness and Adoption Intention ($r > 0.50$, $p < 0.01$), a correlation above 0.50 indicates a moderate-to-strong association between organizational digital readiness and adoption intention. Pharmacies with better technological infrastructure, trained staff, and digital familiarity demonstrate greater openness to implementing Expert Systems.

This aligns with the Technology–Organization–Environment (TOE) framework, which emphasizes organizational preparedness as a key determinant of innovation adoption.

Collectively, these correlation results confirm that usefulness, trust, and readiness are central drivers of digital transformation in pharmaceutical retail management.

While correlation establishes association, regression analysis determines predictive power and relative influence when variables are examined simultaneously.

On Model Fit ($R^2 > 0.45$), the coefficient of determination (R^2) exceeding 0.45 indicates that more than 45% of the variance in adoption intention is explained collectively by perceived usefulness, trust, and digital readiness.

In behavioural and organizational research, explaining nearly half of adoption variance represents strong explanatory power. This confirms that the model captures the core determinants influencing Expert System adoption decisions.

Perceived usefulness emerges as the strongest predictor of adoption intention. A standardized beta coefficient exceeding 0.40 indicates substantial predictive influence when controlling for other variables. The highly significant p-value ($p < 0.001$) demonstrates extremely strong statistical confidence. This means that improvements in perceived usefulness correspond to meaningful increases in adoption intention.

This result robustly validates TAM's central proposition: users adopt technologies primarily when they perceive clear performance benefits.

Practically, this implies that demonstrating measurable improvements in stock accuracy, reduced wastage, and better forecasting will significantly accelerate adoption.

Trust also significantly predicts adoption intention, though at a moderate level relative to usefulness. A beta above 0.25 suggests that even when usefulness is accounted for, trust independently contributes to adoption decisions. This highlights a critical insight: users may recognize system benefits, but without trust in algorithmic outputs, adoption may stall.

For Expert driven inventory systems, transparency, explainability, and reliability mechanisms are therefore essential implementation strategies.

Digital readiness demonstrates a statistically significant but comparatively smaller effect. This indicates that infrastructure and digital familiarity matter, but they do not override perceived performance benefits. In practical terms, even organizations with moderate readiness may adopt the system if perceived usefulness and trust are sufficiently high.

The combined findings present coherent narratives. Perceived usefulness is the dominant driver of adoption. Trust enhances confidence in system-generated decisions. Digital readiness facilitates implementation but is secondary to performance perception. The model explains a substantial proportion of adoption behavior ($R^2 > 0.45$), indicating strong theoretical and empirical validity.

These results empirically validate TAM, UTAUT, and TOE assumptions within the pharmaceutical retail context. More importantly, they demonstrate that Expert System adoption is

not primarily constrained by resistance to technology, but by performance perception and confidence in system reliability.
Strategic Implications Implementation strategies should prioritize demonstrating measurable decision accuracy improvements. Trust-building mechanisms (explainable expert outputs, validation testing, pilot trials) are essential. Digital training programs should accompany system deployment to strengthen readiness. Policymakers and pharmacy regulators can leverage these findings to promote expert-enabled sustainable healthcare operations.
The statistical evidence confirms that intelligent inventory optimization systems are both technically viable and behaviorally acceptable within pharmaceutical retail organizations. Adoption is not speculative. It is strongly predicted by performance belief, trust, and readiness.
These findings position Expert Systems not merely as technological tools, but as strategic enablers of sustainable pharmaceutical supply chain transformation.

Proposed Expert System Framework

The study proposes an integrated Expert System architecture consisting of Data Acquisition Layer, Sales records, Supplier performance data, Inventory logs, Knowledge Base, Reorder rules, Expiry thresholds, Regulatory constraints, Inference Engine, Rule-based reasoning Predictive analytics module, Machine Learning, Forecasting Engine, Seasonal demand prediction, Consumption trend modeling, User Interface Dashboard, Real-time stock alerts, Procurement recommendations, and Risk indicators. This framework supports proactive, data-driven pharmaceutical inventory optimization.

Limitations and Future Research

Cross-sectional design limits causal inference. Self-reported perceptions may introduce bias. Post-implementation performance impact not measured. Future studies should employ longitudinal designs and evaluate cost-benefit performance metrics following system deployment.

CONCLUSION

This study provides strong empirical evidence that pharmaceutical retail organizations face persistent inventory inefficiencies but demonstrate high readiness and willingness to adopt Expert Systems. The strong behavioral intention observed suggests that intelligent decision-support technologies can significantly enhance medicine availability, reduce wastage, and strengthen healthcare supply chain resilience.
The integration of predictive analytics, automated alerts, and rule-based reasoning within an Expert System framework offers a viable pathway toward sustainable pharmaceutical retail management in developing economies.

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