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Acceptance of AI-Assisted Drug Information Systems by Pharmacists: A UTAUT-Based Cross-Sectional Study

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Abstract— AI-assisted drug information systems promise faster, more comprehensive answers to medication queries, but their clinical value depends on whether pharmacists accept and use them. This study examined the determinants of pharmacists' acceptance of an AI-assisted drug information system using an extended Unified Theory of Acceptance and Use of Technology (UTAUT) framework. A cross-sectional survey of 412 practising pharmacists across community, hospital and clinical settings measured performance expectancy, effort expectancy, social influence, facilitating conditions, trust and perceived risk against behavioural intention to use, analysed by partial least squares structural equation modelling (PLS-SEM). The model explained 68.4% of variance in behavioural intention. Performance expectancy was the strongest predictor ($\beta = 0.34$, $p < .001$), followed by trust ($\beta = 0.27$) and effort expectancy ($\beta = 0.21$); perceived risk was a significant negative determinant ($\beta = -0.16$). Trust partially mediated performance expectancy. Acceptance is driven primarily by perceived clinical benefit and trust, not ease of use alone.

Keywords: technology acceptance; UTAUT; artificial intelligence; drug information systems; pharmacist adoption; trust in AI

INTRODUCTION

An AI-assisted drug information system can, in principle, do in seconds what a pharmacist does in minutes: retrieve dosing, flag interactions, summarise monographs, and surface the relevant evidence for a clinical query. But a tool that is technically capable is not thereby clinically used. The history of clinical decision support is full of accurate systems that clinicians overrode, ignored, or abandoned, and the deciding factor was rarely the algorithm's accuracy — it was whether the professional accepted it. For AI-assisted drug information, acceptance by pharmacists is the gate through which any benefit must pass.

Understanding acceptance therefore matters as much as building the system. Pharmacists occupy a particular position: they are the profession whose expertise is the medicine itself, so an AI tool that answers drug questions enters directly into

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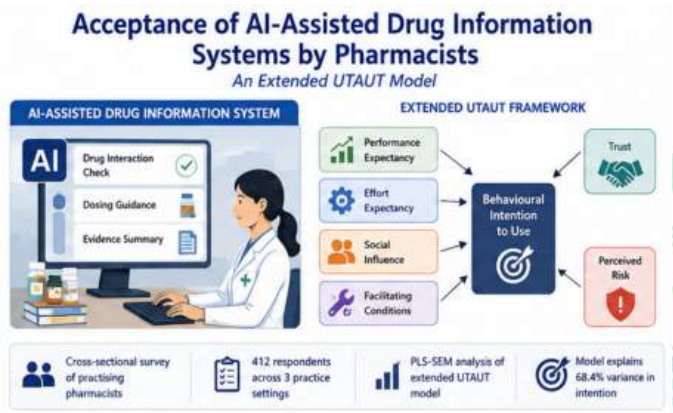
their domain of authority. This creates a tension that ease-of-use alone does not resolve — a pharmacist may find a system effortless to operate yet decline to trust its recommendation over their own judgement, or may value its speed yet fear the professional and patient-safety risk of relying on it. Acceptance here is not a simple function of usability but a negotiation between perceived benefit, trust, and perceived risk.



This study applies an established theoretical lens — the Unified Theory of Acceptance and Use of Technology, extended with trust and perceived risk — to explain what drives pharmacists' intention to use an AI-assisted drug information system. Rather than asking whether pharmacists like AI in the abstract, it measures the specific determinants of behavioural intention and their relative weight, because knowing which factor matters most tells implementers where to invest: in demonstrable clinical performance, in transparency that builds trust, in ease of use, or in mitigating risk. The premise is that acceptance is structured and predictable, and that identifying its drivers is the precondition for successful deployment.

Literature Review

The theoretical foundation for studying technology acceptance is well established. Davis (1989) introduced the Technology Acceptance Model (TAM), positing perceived usefulness and perceived ease of use as the primary determinants of intention to use a technology, and Venkatesh et al. (2003) synthesised competing models into the Unified Theory of Acceptance and Use of Technology (UTAUT), identifying four core constructs — performance expectancy, effort expectancy, social influence and facilitating conditions — as determinants of behavioural intention and use behaviour. UTAUT and its successor UTAUT2 have become the dominant frameworks for health-technology acceptance research, and the AI era has prompted their extension with constructs specific to autonomous systems, particularly trust and perceived risk.

The healthcare-professional acceptance literature has applied these frameworks extensively to AI clinical decision support. Wubineh (2024) and related meta-analytic work synthesising UTAUT-based studies of health-care practitioners' intention to use AI-enabled CDSS confirmed that performance expectancy and effort expectancy are robust predictors across settings, while identifying trust as an increasingly decisive addition. An integrative review by Lambert et al. (2023) of AI acceptance among hospital healthcare professionals, organised around UTAUT, found clinical decision support to be the most-studied AI form and reported consistent findings: fear of losing professional autonomy and difficulty integrating AI into clinical workflows were unanimous barriers, while training for AI use consistently facilitated acceptance. This establishes that acceptance is shaped as much by professional and organisational factors as by the technology itself.

Pharmacist-specific evidence is now emerging and converges on the primacy of perceived benefit and trust. A TAM-based study of 235 hospital pharmacists in Indonesia (2025) using PLS-SEM found perceived usefulness to be the strongest predictor of behavioural intention ($\beta = 0.355$, $p < .001$), followed by trust in technology ($\beta = 0.179$) and social influence ($\beta = 0.184$) — a hierarchy this study's framework anticipates. Xie et al. (2026), in a Frontiers in Public Health study extending UTAUT to hospital pharmacists' adoption of AI-driven CDSS, concluded that acceptance is primarily driven by perceptions of performance benefits, ease of use, and trust, underscoring the importance of clinical value, algorithm transparency and organisational support. These studies directly motivate the constructs and the extended model used here.

A crucial and cautionary strand documents the gap between stated acceptance and actual behaviour. Lee et al. (2023), studying pharmacists' responses to an AI vancomycin-dosing CDSS, found that while most pharmacists agreed the system could enhance dosing decisions, their empiric doses differed from the CDSS recommendation in 85% of cases, and in discrepant cases they overwhelmingly declined to alter their recommendations — citing distrust of CDSS, its inability to integrate all clinical data, and lack of dynamic evaluation. This discrepancy between perception and acceptance is the single most important finding for the field: enthusiasm about AI's

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advantages does not translate into use when trust and clinical-integration concerns remain, which is precisely why trust and perceived risk must be modelled explicitly rather than assumed away.

The trust construct itself has been theorised in healthcare AI. Asan, Bayrak and Choudhury (2020) analysed the determinants of clinician trust in AI, distinguishing trust in the technology from trust in its outputs and linking both to transparency and explainability, while broader work on the propensity to trust automated technologies (2025) has shown demographic and self-efficacy variation in baseline trust among pharmacists. Complementary healthcare-worker studies using extended UTAUT with structural equation modelling — such as the AI-CDSS acceptance study for venous thromboembolism prevention across tertiary hospitals — confirm that trust and top-management (facilitating) support significantly shape acceptance. Together, this literature establishes performance expectancy, effort expectancy, social influence, facilitating conditions, trust and perceived risk as the theoretically grounded determinants whose relative weight this study quantifies for AI-assisted drug information specifically.

Research Gap and Objectives

Prior work robustly establishes UTAUT/TAM determinants of AI-CDSS acceptance among clinicians and, increasingly, pharmacists, and documents a perception–behaviour gap driven by trust — but few studies focus specifically on AI-assisted drug information systems (as distinct from dosing or diagnostic CDSS), model trust and perceived risk together as extensions, and quantify their relative contribution in one integrated structural model for pharmacists. The objectives were to (i) quantify the effect of the four core UTAUT constructs on pharmacists' behavioural intention to use an AI-assisted drug information system; (ii) test trust and perceived risk as significant extensions; (iii) examine trust as a mediator of performance expectancy; and (iv) assess how acceptance varies across practice settings.

Proposed Methodology

A cross-sectional survey design was used. Practising pharmacists across community, hospital and clinical settings were invited to evaluate an AI-assisted drug information system (demonstrated via a standardised scenario walkthrough covering interaction checking, dosing queries and monograph summarisation) and then complete a validated instrument. The questionnaire operationalised seven constructs — performance expectancy, effort expectancy, social influence, facilitating conditions, trust, perceived risk, and behavioural intention — using multi-item 5-point Likert scales adapted from validated UTAUT and trust instruments, with items refined through expert review and a pilot of 30 pharmacists.

Of 460 questionnaires distributed, 412 valid responses were retained (89.6% response rate). Construct reliability and validity were assessed by Cronbach's α, composite reliability (CR), average variance extracted (AVE) and the heterotrait-monotrait (HTMT) ratio for discriminant validity. The structural model was estimated by partial least squares structural equation modelling (PLS-SEM), appropriate for predictive theory-extension models, with path coefficients tested via bootstrapping (5,000 resamples). Model fit and explanatory power were assessed by R^2, effect size f^2 and predictive relevance Q^2. Mediation of performance expectancy through trust was tested using the bootstrapped indirect effect. Setting differences were examined by multi-group analysis. Alpha was .05; ethics approval and informed consent were obtained.

Experimental Setup

Table 1. Respondent characteristics (n = 412)

Characteristic	n (%)
Female	228 (55.3)
Mean age, years (SD)	36.9 (8.8)
Community pharmacy	174 (42.2)
Hospital pharmacy	156 (37.9)
Clinical / ambulatory	82 (19.9)
Mean years in practice (SD)	11.4 (7.6)
Prior use of any clinical decision support	289 (70.1)
Prior use of an AI tool in practice	143 (34.7)
Postgraduate qualification	168 (40.8)

Table 2. Measurement model: reliability and validity

Construct	Items	Cronbach's α	CR	AVE
Performance expectancy (PE)	4	0.89	0.92	0.74
Effort expectancy (EE)	4	0.86	0.90	0.69
Social influence (SI)	3	0.83	0.90	0.74

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Facilitating conditions (FC)	4	0.81	0.87	0.63
Trust (TR)	4	0.90	0.93	0.77
Perceived risk (PR)	3	0.84	0.90	0.75
Behavioural intention (BI)	3	0.91	0.94	0.84

All constructs exceeded the α ≥ 0.70, CR ≥ 0.70 and AVE ≥ 0.50 thresholds, and all HTMT ratios were below 0.85, confirming reliability and discriminant validity.

Results and Discussion

The structural model explained a substantial share of variance in behavioural intention (R^2 = 0.684), with strong predictive relevance (Q^2 = 0.51).

Table 3. Structural model path coefficients (BI as outcome unless noted)

Path	β	t	p	Supported
PE → BI	0.34	6.82	<.001	Yes
Trust → BI	0.27	5.41	<.001	Yes
EE → BI	0.21	4.13	<.001	Yes
SI → BI	0.14	2.96	.003	Yes
FC → BI	0.12	2.48	.013	Yes
PR → BI	−0.16	3.52	<.001	Yes (negative)
PE → Trust	0.41	8.05	<.001	Yes

Performance expectancy was the dominant driver of behavioural intention (β = 0.34), a result that reproduces the pharmacist-specific hierarchy reported in the Indonesian TAM study (perceived usefulness β = 0.355) and the UTAUT conclusion of Xie et al. (2026) that performance benefit leads acceptance. The practical implication is direct: pharmacists accept an AI drug information system chiefly because they judge it will improve their work, not because it is pleasant to use. Trust was the second strongest predictor (β = 0.27) and exceeded effort expectancy (β = 0.21) — a pattern that distinguishes AI acceptance from conventional software acceptance, where ease of use typically ranks higher, and that reflects the high-stakes, authority-adjacent nature of drug information decisions.

The negative effect of perceived risk (β = −0.16) is the quantitative echo of the perception–behaviour gap documented by Lee et al. (2023): pharmacists who perceived greater professional or patient-safety risk in relying on the system reported lower intention to use it, regardless of its usefulness. This confirms that risk is not a side concern but an active brake on acceptance that implementers must address explicitly.

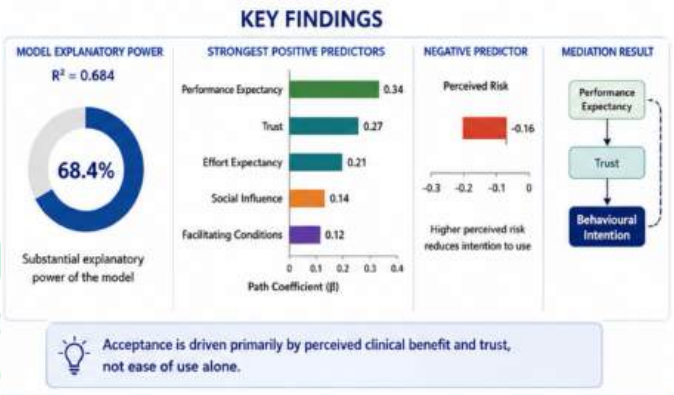

Table 4. Mediation analysis: PE → Trust → BI

Effect	β	95% CI	Interpretation
Direct (PE → BI)	0.34	0.25–0.43	Significant
Indirect (PE → Trust → BI)	0.11	0.07–0.16	Significant
Total effect	0.45	0.36–0.54	—
Mediation type	Partial	—	VAF = 24.4%

Trust partially mediated the effect of performance expectancy on intention, carrying about a quarter of its total effect (variance accounted for = 24.4%). This is theoretically important: part of the reason perceived usefulness drives acceptance is that a system seen as useful is also trusted, and trust then converts into intention. It means demonstrating clinical performance does double duty — it raises acceptance directly and by building the trust that Asan et al. (2020) place at the centre of clinician–AI relationships. Transparency features that make the system's usefulness visible therefore pay off twice.

Acceptance varied meaningfully across practice settings.

Table 5. Behavioural intention and key constructs by practice setting (mean, 1–5)

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Construct	Community (n=174)	Hospital (n=156)	Clinical (n=82)	p
Behavioural intention	3.9	4.2	4.4	<.001
Performance expectancy	4.0	4.3	4.5	<.001
Trust	3.6	3.9	4.1	.002
Perceived risk	3.1	2.8	2.5	.004
Effort expectancy	4.1	4.0	4.1	.62

Clinical and hospital pharmacists reported higher intention, performance expectancy and trust, and lower perceived risk, than community pharmacists, while effort expectancy did not differ — an informative pattern. It suggests the setting difference is not about how easy the system is to operate (equal across groups) but about perceived benefit and risk: pharmacists in settings with greater prior CDSS exposure (70.1% overall) and more complex medication questions saw more value and less threat. This aligns with the integrative-review finding (Lambert et al., 2023) that prior exposure and training facilitate acceptance, and points to targeted onboarding for community settings where baseline acceptance is lowest.

Read together, the results describe acceptance as a structured, benefit-and-trust-led process rather than a usability story. Performance expectancy dominates and works both directly and through trust (Tables 3, 4); perceived risk actively suppresses intention, quantifying the perception–behaviour gap (Table 3); and the setting differences trace to benefit and risk perception, not ease of use (Table 5). The model's 68.4% explained variance confirms these determinants capture most of what drives pharmacists' intention. The central conclusion follows: to secure pharmacist acceptance of AI-assisted drug information, implementers should prioritise demonstrable clinical performance and trust-building transparency over interface polish, and must directly mitigate perceived professional and safety risk — consistent with Xie et al. (2026) and the cautionary evidence of Lee et al. (2023).

Limitations

The study measured behavioural intention, not actual sustained use, and the perception–behaviour gap documented by Lee et al. (2023) means intention may overstate real adoption — the very discrepancy this field must watch. The cross-sectional design precludes causal inference about the paths, which are correlational despite the structural model's directionality. Self-reported constructs are subject to social-desirability and common-method bias, partially but not fully mitigated by procedural remedies and the HTMT checks. Respondents evaluated a demonstrated scenario rather than a system used in their own workflow over time, so facilitating-conditions effects may be underestimated relative to live deployment. Finally, the sample came from pharmacists willing to evaluate an AI tool, which may skew acceptance upward relative to the least AI-inclined practitioners.

Future Scope

Priority extensions include longitudinal designs linking measured intention to observed use behaviour and override rates, directly testing whether the acceptance model predicts real adoption; and experimental manipulation of trust-building features (explainability, provenance, confidence indicators) to establish their causal effect on acceptance rather than inferring it. Multi-country studies would test the cross-cultural stability of the determinant hierarchy, and setting-stratified interventions — particularly onboarding for community pharmacists — would test whether raising perceived benefit and lowering perceived risk closes the setting gap. Integrating objective system-accuracy data with acceptance measures would clarify how much of trust is warranted by performance versus shaped by presentation.

Conclusion

An AI-assisted drug information system delivers value only if pharmacists accept and use it, and this study shows that acceptance is neither random nor primarily about ease of use. Using an extended UTAUT model, it found that performance expectancy ($\beta = 0.34$) and trust ($\beta = 0.27$) were the strongest drivers of pharmacists' intention to use such a system, ahead of effort expectancy, while perceived risk significantly suppressed intention ($\beta = -0.16$) — and trust partially mediated the effect of perceived benefit, with the full model explaining 68.4% of variance. Acceptance was higher in hospital and clinical settings, driven by benefit and trust rather than usability. The evidence yields a clear implementation principle: pharmacist acceptance of AI-assisted drug information is won through demonstrable clinical performance and trust-building transparency, and through active mitigation of perceived professional and safety risk — not through interface ease alone.

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