RESEARCH ARTICLE

Hospital Pharmacists' Perspectives on Clinical Decision Support Systems: Perceived Usefulness, Barriers, and Willingness to Adopt in Non-Implementing Hospitals in Rizal Province, Philippines

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Abstract

Clinical decision support systems (CDSS) can improve medication safety, yet implementation remains limited in some Philippine hospitals. This study examined hospital pharmacists' perceived usefulness of CDSS, willingness to adopt, trust requirements, and anticipated barriers in non-implementing hospitals in Rizal Province, Philippines. A convergent mixed-methods, cross-sectional survey was conducted among 84 licensed hospital pharmacists using a content-validated 15-item Likert questionnaire and six open-ended questions, analysed descriptively and thematically. Across perceived-usefulness items, 88.10%–92.86% agreed that CDSS could improve medication safety, risk detection, and efficiency. Trust was conditional on transparency: 82.14%–85.71% reported greater trust or willingness when systems provided clinical rationales, evidence links or grading, and auditable calculation pathways. Although no respondent's hospital had a CDSS, 78.57% reported a general tendency to override electronic alerts from other tools to maintain clinical speed; this is not a CDSS override rate but signals a risk if future notifications are poorly stratified. Self-reported CDSS knowledge was not associated with age (Fisher-Freeman-Halton exact test, $p = 0.389$). The main barriers were software and infrastructure costs (86.90%) and insufficient IT support (82.14%); qualitative findings added paper-based infrastructure, budget constraints, understaffing, and demands for low-friction interfaces, tiered alerting, and preserved professional judgment. Pharmacists viewed CDSS as useful and were conditionally willing to adopt it. Implementation should prioritize technical support, transparent recommendations, and workflow-compatible alert design.

Keywords: clinical decision support systems, hospital pharmacists, technology acceptance, implementation barriers, medication safety, Philippines.

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1 Introduction

The rapid evolution of digital health technology has led to the widespread implementation of clinical decision support systems (CDSS), which are designed to enhance patient safety by providing clinicians with real-time, evidence-based recommendations [1]. When effectively integrated within electronic health records (EHR) and computerized physician order entry (CPOE) systems, these tools serve as a critical defence against medical errors [2]. However, the success of such systems depends heavily on technical synchronization and the quality of the user interface; poorly optimized systems often result in fragmented data and "black box" algorithms that lack transparency, reducing clinician trust and engagement [1, 3].

Despite the potential of CDSS to enhance clinical accuracy, standardize care, and support evidence-based practice, a number of hospitals have not implemented such systems [4]. This situation raises critical questions regarding institutional readiness, perceived usefulness, and the strategic prioritization of digital health technologies [1]. While CDSS is designed to improve efficiency and decision quality, concerns persist regarding infrastructure capacity, financial sustainability, integration with existing systems, and clinical acceptance; in addition, workflow disruptions contribute to delayed adoption [5, 6]. Examining these factors is essential to understand whether non-implementation stems from structural limitations, organizational resistance to technological transformation, or cautious evaluation of the system's real-world value in improving patient outcomes and healthcare delivery efficiency [4].

In the broader context of clinical decision-making, the role of CDSS is increasingly vital [1]. Modern healthcare environments demand precise, evidence-based decisions supported by accurate and timely patient data, and CDSS has the potential to guide clinicians toward safer and more efficient care [2]. However, its impact is reduced when the system is not well integrated into clinical workflows or aligned with user needs; addressing knowledge gaps and improving system usability are therefore essential steps in strengthening clinician engagement and promoting informed, technology-supported decision-making [3, 7].

This study examines hospital pharmacists' perspectives on the perceived usefulness of, barriers to, and willingness to adopt CDSS in non-implementing hospitals in Rizal Province, Philippines. Using a convergent mixed-methods survey, it evaluates the perceived effectiveness of CDSS in enhancing clinical decision-making and patient safety, assesses pharmacists' readiness to use these systems, and identifies the organizational and perceptual obstacles that might hinder implementation. The results are intended to inform future CDSS implementation strategies and support the progress of digital healthcare practice in hospital environments.

1.1 Statement of the Problem

CDSS are intended to support accurate and timely clinical decision-making. However, adoption remains limited in some hospital settings, particularly among hospital pharmacists. Uncertainty regarding the perceived usefulness of CDSS, concerns about workflow compatibility and system complexity, and limited trust in AI-generated recommendations may influence pharmacists' willingness to adopt such systems. Organizational and perceptual barriers may further hinder implementation, preventing hospitals from fully integrating digital decision-support technologies. Examining perceived usefulness, willingness to use, and barriers to adoption is therefore essential to guide future CDSS implementation and digital health strategies in hospital practice.

1.2 Research Gap

Despite rapid advances in data analytics and artificial intelligence (AI) in clinical settings, several gaps continue to limit the effective adoption of CDSS. Existing literature has largely focused on technological improvements, while less attention has been given to the organizational and perceptual factors that influence implementation in hospitals. Concerns about workflow disruption, system complexity, interoperability with existing systems, and the trustworthiness of AI-generated recommendations may affect how CDSS is viewed and whether it is adopted. Research also remains limited on how hospital pharmacists perceive the usefulness of CDSS and which factors influence their willingness to adopt such systems, particularly in hospitals where CDSS has not yet been implemented. This study addresses these gaps by examining hospital pharmacists' perceived usefulness of CDSS, their willingness to adopt it, and the barriers that may shape implementation decisions.

1.3 Objectives and Research Questions

The main objective of this study is to examine hospital pharmacists' perceptions of the potential usefulness

of CDSS in hospitals where such systems are not yet implemented, to assess their willingness to adopt CDSS if introduced, and to identify organizational, practical, and perceptual barriers that may hinder implementation. The specific objectives are:

(1) to examine hospital pharmacists' perceptions of the potential usefulness of CDSS in supporting clinical decision-making and improving workflow efficiency;

(2) to identify anticipated barriers to adopting CDSS, including issues related to system integration, workflow friction, and the interpretability of AI-driven recommendations; and

(3) to explore hospital pharmacists' willingness to adopt CDSS in future practice and the conditions under which they would trust system outputs (e.g., clinical rationale, evidence links, and auditability).

The specific research questions were as follows.

RQ1. *Perceived usefulness* (*quantitative focus*). (a) How do hospital pharmacists perceive the potential usefulness of CDSS in supporting clinical decision-making? (b) To what extent do they believe that CDSS alerts and recommendations could enhance the accuracy and efficiency of patient care?

RQ2. *Willingness to use* (*quantitative and qualitative focus*). (a) To what extent are pharmacists willing to rely on CDSS recommendations, and under what conditions? (b) How do practitioners perceive the "black box" nature of CDSS, and what explanations do they require to trust machine-generated logic?

RQ3. *Barriers.* What are the primary perceived barriers to the future integration of CDSS into pharmacists' clinical workflow?

The study was designed as a descriptive, pre-implementation assessment; the research questions were therefore addressed with descriptive statistics and thematic analysis rather than with formal hypothesis tests. In addition, the association between respondents' age and their self-reported level of CDSS knowledge was examined as an exploratory analysis (Section 5.2).

1.4 Significance of the Study

The findings provide insights into hospital pharmacists' perceptions of the usefulness of CDSS in supporting clinical decision-making and improving workflow efficiency, identify barriers that may hinder adoption, and examine factors that influence willingness to adopt. The results may assist system developers in improving usability and user acceptance, help hospital administrators and policymakers design informed implementation strategies, and contribute to future research on digital health adoption in hospital pharmacy practice.

Hospital pharmacists. By identifying perceived barriers and clinical expectations before implementation, the study provides a proactive framework to ensure that future systems are intuitive and supportive, allowing pharmacists to focus on complex medication therapy and direct patient care rather than on poorly integrated alerts or redundant notifications.

Patients and healthcare consumers. By establishing parameters for system transparency and workflow integration prior to deployment, the study helps ensure that future CDSS implementations act as a reliable safety net rather than a source of professional friction. Mitigating cognitive overload allows pharmacists to maintain situational awareness, which may reduce medication errors and adverse drug events (ADEs).

Hospital administrators and policymakers. The study offers a basis for effective implementation and optimization of digital health investments. Administrators can use the findings to develop hospital-wide protocols for CDSS management, supporting a return on investment (ROI) in terms of both financial savings (by preventing costly medical errors) and clinical efficiency.

Software developers and IT engineers. The research provides empirical data on clinician engagement and human-computer interaction (HCI). By understanding "black box" concerns and usability frustrations, developers can design CDSS with improved interoperability and explainable AI (XAI) features that are more likely to be adopted in real-world clinical settings.

The academic and scientific community. The study shifts the focus of health informatics research from purely technological advancement to a multidimensional approach that includes human factors, adding to the body of knowledge on technology acceptance in high-stakes environments.

Regulatory and standard-setting bodies. By identifying perceived risks of workflow disruption and cognitive

overload, the results may assist regulators in establishing localized guidelines for system transparency and operational readiness that prioritize pharmacist-centred usability and evidence-based AI logic.

2 Review of Related Literature

Data analytics is an integral component of CDSS, a technology that assists healthcare providers in making informed, data-driven clinical decisions. CDSS can improve patient care through recommendations on diagnosis, treatment, and medication management, drawing on large volumes of data such as EHRs, disease registries, and patient surveys. However, high volumes of data and digitalization in healthcare do not necessarily translate into better patient outcomes; high-quality clinical decision support is needed to realize the full benefits of EHR and CPOE systems [1, 8].

Hospitals began using the earliest forms of computerized patient information systems in the 1960s; for example, a pharmacist could receive a warning that a prescription might cause a dangerous drug interaction [9]. Over time, these systems evolved toward more data-intensive analysis and knowledge-based diagnostic programs such as INTERNIST-I, which generated probabilistic differential diagnoses. Although early systems such as INTERNIST-I and its successor CADUCEUS were limited by their knowledge bases and diagnostic sensitivity, they established the conceptual foundation for subsequent generations of clinical AI tools; a retrospective analysis of thirty years of AI-in-medicine research confirms that knowledge-based diagnosis and decision support have remained defining themes throughout this evolution [10].

The philosophical approach of CDSS focuses on aligning clinician expertise with AI-generated recommendations. A primary concern is clinicians' possible over-reliance on data-driven tools, which may undermine experiential decision-making. Practitioners need to remain vigilant, viewing technology as a complement to–rather than a substitute for–professional expertise. Ongoing discussions focus on advisory versus directive AI outputs, especially in critical areas such as diagnostics and treatment guidelines [11].

The number of CDSS implementations has gradually increased over the years. A study at Lille University Medical Center showed how integrating a CDSS (PharmaClass®) into a clinical pharmacy team's workflow supported the detection of drug-related problems and medication management [12]. More broadly, the application of CDSS across medicine, particularly in pharmacotherapy, has been associated with reductions in medication errors and ADEs [13]. Systems that automatically generate alerts for potential drug interactions while minimizing workflow disruption reflect a broader trend toward more user-centred CDSS in routine clinical practice.

Evidence-based medicine (EBM) serves as a fundamental theoretical foundation for CDSS, enabling the incorporation of validated clinical evidence into everyday patient care. Machine-readable knowledge bases and computational models have been crucial in enhancing CDSS functions, allowing individual patient data to be compared with established evidence to produce actionable suggestions. These systems grow in complexity as they integrate newly available clinical evidence, keeping recommendations in line with current medical understanding [14].

Despite this progress, numerous challenges still affect CDSS implementation. Concerns about system complexity, workflow disruption, and confidence in AI-generated suggestions can affect healthcare professionals' readiness to embrace these systems. Ensuring dependable data integration and compatibility with existing healthcare information systems remains crucial for hospitals assessing CDSS implementation, and further refinement is required to improve usability, reliability, and user acceptance in practical settings [5, 15].

A key theoretical concern in CDSS development is that machine-learning models should be transparent and their recommendations intelligible. Explainable AI (XAI) has emerged as a strategy to make CDSS output understandable to healthcare providers by indicating how recommendations are derived [16]. Practically, alerts must balance timely relevance against disruption so that they do not degrade clinician workflows [17].

Studies have shown the capability of CDSS to improve clinical outcomes, especially medication safety. Systems that identify drug-drug interactions and provide dosing recommendations have been shown to reduce prescribing errors substantially [13]. By contrast, the success of CDSS implementation depends largely on the active involvement of clinicians, the usability of the system, and the quality of the underlying data [15].

2.1 Evolution and Development of Integrated CDSS

The origins of CDSS trace back to the 1950s-1960s, with pioneering work on computer-aided diagnosis and early medication decision tools, including Lawrence Weed's problem-oriented medical record [18]. Bates et al. [19] argued in their "Ten Commandments" for effective CDSS that speed is paramount and that decision support must anticipate needs and fit into the user's workflow in real time; failure to do so is a major reason clinicians abandon these systems. Donovan et al. [20] conducted a systematic review of implementation costs associated with hospital-based CDSS, finding that financial investment varies substantially across system types and settings and that cost transparency remains a significant barrier to wider adoption.

2.2 Barriers, Facilitators, and User Acceptance of CDSS

Understanding why CDSS adoption succeeds or fails requires examining both organizational and individual factors. A NASSS framework-informed scoping review identified a broad spectrum of barriers and facilitators to successful CDSS implementation in hospitals, including system complexity, workflow integration challenges, staff engagement, and institutional readiness [21]. At the individual level, pharmacists' willingness to adopt AI-driven CDSS is shaped by constructs beyond simple intention: an extended UTAUT analysis revealed that performance expectancy, effort expectancy, social influence, and trust in AI output jointly explain adoption behaviour among pharmacy professionals [22]. Complementing this, a TAM-based study focused specifically on hospital pharmacists found that perceived usefulness and perceived ease of use significantly predict adoption intentions toward AI-based clinical decision support tools, underscoring the applicability of acceptance-model frameworks to this professional group [23].

2.3 Artificial Intelligence and Machine Learning in CDSS

AI and machine learning allow CDSS to "learn" from previous clinical cases and identify patterns imperceptible to the human eye [24]. However, the "black box" nature of AI creates a trust gap. Miller and Brown [25] note that AI must earn clinicians' confidence before it is accepted in clinical practice, and that its outputs require clinical interpretation. Topol [26] describes an era of "high-performance medicine" in which AI-driven tools may reduce clinicians' clerical burden and free time for the human aspects of care, provided that the systems are interpretable.

2.4 Medication Management and Alert Fatigue

Medication management remains the most successful application of CDSS, particularly for identifying drug-drug interactions [13]. Kawamoto et al. [27] conducted a landmark systematic review showing that CDSS is most effective when it provides recommendations automatically as part of the clinician workflow rather than requiring clinicians to seek them out. However, a large proportion of CDSS alerts are overridden, and alert acceptance declines as workload and alert repetition increase, highlighting a crisis in alert relevance [28]. Human-factors principles for medication alerts–such as consistent use of colour, placement, and prioritization by severity–can help mitigate fatigue by signalling the actual urgency of a notification [17].

2.5 Human Factors: Usability and Nursing Workflows

For CDSS to achieve optimal effectiveness, seamless workflow integration that does not disrupt daily clinical practice remains essential [8]. Varonen et al. [29] found that physicians considered CDSS useful for evidence-based medicine but potentially disruptive during face-to-face consultations. Randell and Dowding [30] showed that nurses' use of CDSS is strongly shaped by organizational context and by the dynamic nature of bedside work. Ratwani et al. [31] emphasize that health IT and EHR usability is a matter of patient safety and call for standardized usability testing.

2.6 Impact on Clinical Outcomes and Cost-Effectiveness

The integration of CDSS into practice has shown considerable potential to reduce medical errors, including drug-related problems identified during medication review [13, 32]. Beyond safety, Bright et al. [33] conducted a systematic review showing that CDSS improves the process of care (such as adherence to preventive guidelines), although its impact on long-term clinical outcomes such as mortality remains harder to quantify. Fillmore et al. [34] suggest that optimized CDSS can also reduce costs by preventing expensive complications such as ADEs and unnecessary laboratory tests.

2.7 Technology Acceptance Model

The Technology Acceptance Model (TAM) was developed in the 1980s in response to concern that workers were not using the information technologies made available to them [35]. Its originators reasoned that increasing use first required increasing acceptance, which could be assessed by asking individuals about their intention to use a technology; knowing the factors that shape intention allows organizations to influence them and thereby promote acceptance and use. Early TAM research found that only a small number of factors–chiefly perceived usefulness and perceived ease of use–were needed to explain and predict acceptance [36].

2.8 Patient-Facing Decision Support

With the advent of the personal health record (PHR), CDS functionality is being integrated with the patient as the end user of the data. CDS-supported PHRs can facilitate shared decision-making between patient and provider because they remove lack of information as a barrier to patients' participation in their own care. PHRs are often built as extensions of commercial EHR software or as standalone web-based or mobile applications; when connected to an EHR, information can flow in both directions between patients and providers [18].

2.9 Enhancing Clinical Guideline Adherence via Automated Support

CDSS can increase adherence to clinical guidelines. Traditional guidelines and care pathways are difficult to implement, and the assumption that practitioners will read, internalize, and apply new guidelines has not held true. Rules implicit in guidelines can, however, be encoded in CDSS as standardized order sets, protocol-specific alerts, and testing reminders. CDSS can also help manage patients on research or treatment protocols, track and place orders, follow up referrals, and support preventive care [18].

2.10 Clinical Willingness and System Adaptation

In a qualitative study of Italian hospitals, Liberati et al. [37] described full integration of CDSS as the most advanced stage of uptake: clinicians perceive CDSS as a working tool that complements their skills and critical thinking, IT staff and managers regard it as a milestone of a modern hospital, content is adapted to local clinical contexts, and clinicians become willing to "learn" from the system. Notably, none of the hospitals in that study had yet reached this stage.

2.11 Addressing Ordering Errors via CPOE and CDSS

Analyses of medication errors suggest that prevention strategies targeting systems rather than individuals are most effective. CPOE and CDSS target the ordering stage, where most medication errors and preventable ADEs occur. Despite public mandates and clear theoretical advantages, organizational adoption of these systems has been limited; the Institute of Medicine report *To Err Is Human* highlighted this gap between healthcare and other industries and called for wider adoption of information technology to improve medication safety [13].

2.12 Trust and Resistance to AI-Based CDSS

The integration of AI into CDSS has introduced new concerns regarding trust and transparency. Tonekaboni et al. [38] found that clinicians often hesitate to rely on algorithmic recommendations when the underlying reasoning is not visible or understandable. Holzinger et al. [16] similarly argued that explainability is essential for fostering trust in AI-driven healthcare systems. When clinicians cannot verify how recommendations are generated, they may question the reliability of the system and resist adoption. This "black box" problem remains a significant challenge for AI-powered CDSS [16].

2.13 Implementation Barriers and Facilitators of CDSS

Successful CDSS deployment in hospital settings requires navigating a complex landscape of organizational, technical, and human factors. A systematic scoping review applying the NASSS (Nonadoption, Abandonment, Scale-up, Spread, and Sustainability) framework identified recurring implementation barriers such as poor interoperability with existing hospital information systems, insufficient end-user involvement in system design, inadequate training, and lack of institutional support [21]. The same review highlighted facilitators including strong clinical leadership, iterative co-design with frontline staff, and clear alignment between system capabilities and clinical workflows. These findings reinforce that sustainable CDSS adoption depends not only on technical functionality but also on the socio-organizational context into which the system is introduced [21].

2.14 Adoption and Uptake of CDSS

Although CDSS are increasingly implemented, their actual uptake remains inconsistent. A systematic

review and meta-regression found that only 12.4% of eligible studies reported CDSS uptake, with a pooled uptake of approximately one-third of opportunities; most CDSS were integrated into existing software, delivered advice at the point of care, and were based on disease-specific guidelines [39]. Successful implementation therefore depends not only on system availability but also on the extent to which professionals actively engage with the technology [27, 39]. These findings emphasize seamless integration and workflow compatibility as key factors influencing the effectiveness and acceptance of CDSS.

2.15 An AI-Integrated CDSS: "Brilliant Doctor"

The AI-based CDSS known as "Brilliant Doctor" is integrated into an existing EHR system in a dual-interface layout in which the EHR window and AI support tools are displayed side by side [40]. The EHR section records patient demographics, symptoms, history, allergies, diagnoses, prescriptions, and treatment plans in structured fields, while the AI window provides real-time support by generating ranked diagnostic suggestions with confidence scores, together with treatment, laboratory-test, and medication recommendations. Deployment in rural clinics nevertheless revealed tensions between the system's design and local workflows, resources, and clinician autonomy [40].

2.16 Performance Expectancy and Perceived Risk in AI-CDSS Adoption

Performance expectancy, a key construct of the Unified Theory of Acceptance and Use of Technology (UTAUT), refers to clinicians' belief that using a technology will improve their job performance and is closely related to perceived usefulness in TAM. In the context of AI-CDSS, it strongly influences physicians' acceptance; however, weak human-AI communication and uncertain real-world effectiveness may reduce the perceived benefit. Perceived risk–clinicians' sense of insecurity when using the technology and exchanging data, including concerns about privacy, information leakage, and ethical or legal responsibility–also shapes adoption. Together, these factors significantly influence physicians' willingness to adopt AI in clinical practice [41].

2.17 Synthesis of Related Literature

The reviewed literature highlights the evolution of CDSS from early computer-assisted diagnostic tools to sophisticated AI-driven systems integrated into modern healthcare. Advances in EHRs and machine learning enable CDSS to process large volumes of clinical data and provide real-time recommendations that support diagnosis, medication management, treatment planning, and guideline adherence [18]. Patient-facing tools and AI-integrated platforms further demonstrate the expanding potential of CDSS to engage both providers and patients.

However, successful implementation extends beyond technological advancement. System effectiveness depends on interoperability, integration with existing systems, usability, and compatibility with clinical workflows [8, 31, 39]. Fragmented data sources, poor interoperability, alert fatigue, workflow disruption, and the barriers documented in NASSS-informed implementation reviews can limit user acceptance and reduce the practical benefits of CDSS [21, 28]. As AI is increasingly incorporated into CDSS, concerns about transparency, explainability, trust, data security, and ethical responsibility have emerged; clinicians' inability to understand how AI-generated recommendations are produced may create resistance despite potential benefits [16, 38].

In response, researchers have examined the human and organizational factors influencing CDSS adoption. TAM and UTAUT suggest that healthcare professionals are more likely to adopt CDSS when they perceive it as useful, easy to use, and capable of improving job performance [36, 41]. Although these factors have been studied among physicians and other professionals, limited attention has been given to hospital pharmacists, despite their central role in medication management and safety. Further investigation is therefore needed to assess hospital pharmacists' readiness for CDSS integration and the factors that may support or hinder implementation.

3 Theoretical and Operational Frameworks

This study is grounded in three theories that address the multidimensional nature of CDSS adoption: the Technology Acceptance Model (TAM), Human Factors Engineering (HFE), and Cognitive Load Theory (CLT) (Figures 1, 2, and 3, respectively). The operational framework is summarized in Figure 4.

The primary lens for this study is TAM, which posits that the adoption of health information technology is determined by two cognitive factors: perceived usefulness (PU) and perceived ease of use (PEOU) [35, 36]. Here, PU refers to the pharmacist's belief that an integrated CDSS will tangibly improve medication safety and dosing accuracy, and PEOU refers to the

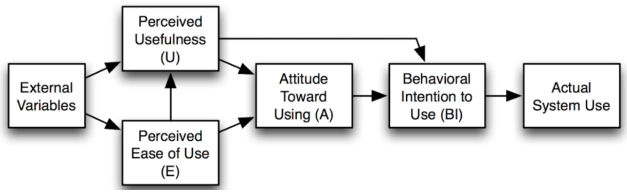

Figure 1. Technology Acceptance Model (TAM). Adapted from Davis [35].

expectation that the system will be intuitive and integrated into existing pharmacy workflows without creating technical friction. Applying TAM, pharmacist readiness is treated as a psychological outcome of how effectively the system is perceived to support professional objectives.

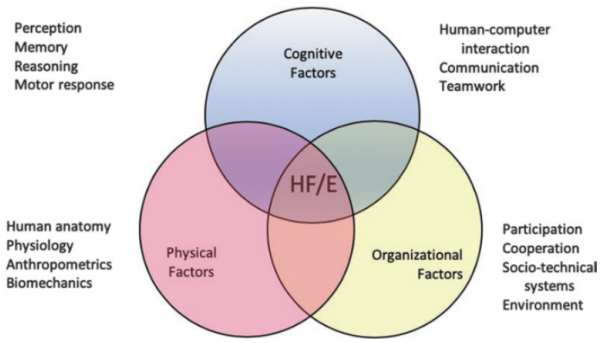

Figure 2. Human Factors Engineering (HFE) domains. Based on the systems approach of Carayon et al. [42].

HFE provides the structural basis for analysing the interaction between pharmacists and the CDSS interface, specifically regarding workflow integration [42]. The framework suggests that the real-world barrier to technology adoption is often a misfit between the digital tool and the practitioner's physical and professional routine. This study uses HFE principles to examine the perceived barrier of workflow disruption, including whether a system might be seen as a hindrance during high-pressure or emergency situations.

CLT is used to analyse the mental strain placed on pharmacists by the extraneous load of complex, non-transparent machine logic [43]. Because working memory is limited, a system that presents recommendations without clear clinical rationales increases the effort required to validate its output. Providing explainable logic may reduce extraneous load, preserving capacity for high-level clinical reasoning and patient safety and thereby mitigating cognitive overload.

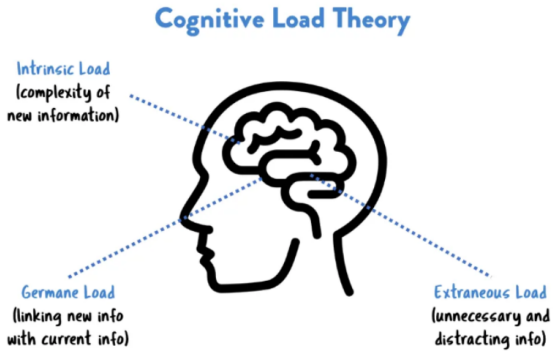

Figure 3. Cognitive Load Theory (CLT): intrinsic, extraneous, and germane load. Based on Sweller [43].

The operational framework uses an input-process-output (IPO) model (Figure 4). The input phase captures professional demographics, technical infrastructure (e.g., current EHR and CPOE integration), and behavioural parameters, including trust and perceptions of the algorithmic "black box". The process phase comprises the mixed-methods procedures: a quantitative stream (instrument validation using I-CVI/S-CVI, internal-consistency testing with Cronbach's α, and statistical readiness analysis) and a qualitative stream (thematic analysis of open-ended responses on workflow disruption and transparency needs). The output phase comprises evidence-based recommendations for CDSS design that minimizes alert fatigue, strategies for clinician engagement through transparent on-screen reasoning, and, ultimately, improved patient safety through fewer medication errors.

4 Methodology

4.1 Research Design and Population

This study used a convergent mixed-methods, cross-sectional survey design. It targeted hospital pharmacists practising in hospitals in Rizal Province, Philippines, that had not yet implemented an integrated CDSS. The target population comprised 84 licensed hospital pharmacists directly involved in clinical decision-making and pharmaceutical care, as they are key stakeholders in potential CDSS adoption. Focusing on this group captures the perspectives of pharmacists at the pre-implementation stage, allowing an authentic assessment of perceived usefulness, anticipated barriers, and willingness to adopt digital tools. Pharmacists from various institutional backgrounds were included regardless of their current level of exposure to AI.

Inclusion criteria were: (a) licensed pharmacist; (b)

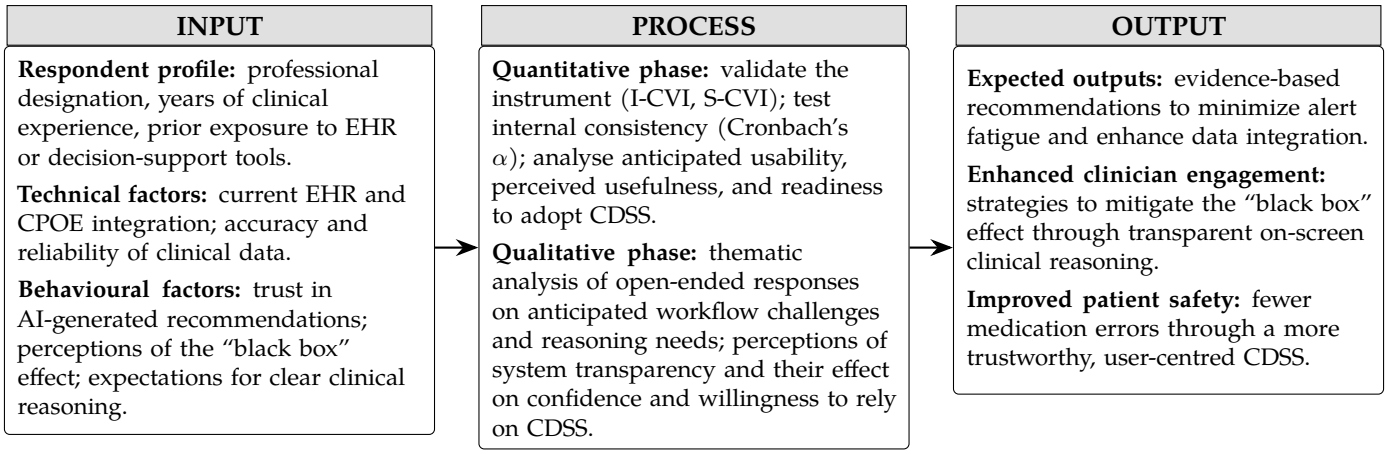

Figure 4. Operational framework of the study: an input-process-output (IPO) model for CDSS readiness assessment.

at least six months of clinical practice; (c) basic awareness of AI or digital health records; (d) current duties including clinical services, medication therapy management, or patient care; and (e) voluntary informed consent. Participation was voluntary; participants could withdraw at any time without penalty and could request removal of their responses before data consolidation and analysis.

4.2 Sample Size and Sampling

Purposive sampling was used to select hospital pharmacists practising in hospitals that had not implemented a CDSS. For the quantitative strand, 84 pharmacists from various healthcare institutions in Rizal Province were recruited. For the qualitative strand, open-ended responses were analysed until thematic saturation was reached, i.e., until no new themes emerged regarding perceived barriers, system transparency, and adoption expectations.

4.3 Research Instrument and Validity

The instrument was a structured questionnaire with five sections. Section 1 collected demographic and professional data (age, gender, years of practice, and comfort with digital healthcare technology/AI). Sections 2-4 each contained five 5-point Likert items (1 = strongly disagree, 2 = disagree, 3 = neither agree nor disagree, 4 = agree, 5 = strongly agree) measuring perceived usefulness (medication safety, clinical efficiency, and dosing accuracy), willingness to use and trust (readiness to adopt AI-driven tools, system transparency, and evidentiary support), and barriers to implementation (financial costs, workflow disruption, alert burden, and IT support). Section 5 contained six open-ended questions on institutional hurdles and trust requirements. Item Q9 ("I frequently override alerts to maintain clinical speed") did not specify the source of the alerts; because no respondent's hospital had an integrated CDSS, responses to this item were interpreted as a general, self-reported tendency in handling electronic medication alerts (Section 5.4) rather than as override behaviour within a CDSS.

Content validity was evaluated by a panel of six experts (two IT system specialists and four hospital pharmacists), who rated each item's relevance on a 4-point scale (1 = not relevant to 4 = highly relevant). The item-level content validity index (I-CVI) was the proportion of experts rating an item 3 or 4; with six experts, items required an I-CVI ≥ 0.83 (agreement of at least five of six experts) for retention. The scale-level content validity index (S-CVI/Ave) was calculated, with ≥ 0.90 considered acceptable [44]. A pilot test was conducted among hospital pharmacists practising outside Rizal Province to evaluate clarity and feasibility without contaminating the study sample.

4.4 Data Collection

The validated instrument was distributed to 84 hospital pharmacists in Rizal Province using a dual approach suited to the diverse infrastructure and demanding schedules of participating institutions: an online form (Google Forms) and printed questionnaires delivered to hospital pharmacy departments. The questionnaire took 10-15 minutes to complete, and items were arranged to minimize order bias.

4.5 Ethical Considerations

The study protocol was reviewed and approved by the Philippine Women's University Ethics Review Board (ERB Protocol No. ERB 2020_008; Certificate of Approval dated 12 March 2026) before data collection began. Written informed consent was obtained from all participants. An informed-consent form

presented at the beginning of both the online and the printed questionnaire explained the purpose of the study, the nature of participation, the data-collection procedures, potential benefits and risks, and the intended use of the data; respondents could proceed to the survey items only after voluntarily giving consent. Participation was voluntary, participants could withdraw at any time without penalty, and responses were anonymized so that they could not be traced to individual participants or institutions. Data were stored on a password-protected drive accessible only to the researchers, in accordance with Republic Act No. 10173 (Data Privacy Act of 2012). The study involved no clinical procedures or interventions and posed minimal risk to participants.

4.6 Data Analysis

Table 1. Cronbach's alpha internal consistency reliability of the survey scale.

Scale metric	Value
Number of items (n)	15
Average inter-item covariance	0.1832
Scale reliability coefficient (α)	0.8444

Note. Item q12 was reverse-coded prior to analysis. A Cronbach's α of 0.8444 falls within the 0.80-0.89 range conventionally interpreted as good internal consistency.

Internal consistency of the 15-item scale was assessed with Cronbach's α (Table 1). Item q12 was reverse-coded for this analysis to maintain directional alignment. Quantitative data were summarized using frequencies, percentages, means, standard errors (SE), and 95% confidence intervals (CIs). Item means were interpreted descriptively within their respective constructs; higher scores indicated stronger agreement with the wording of each item. The association between age and self-reported level of CDSS knowledge was examined as an exploratory analysis. Because the full age-by-response cross-tabulation (17 single-year ages $\times$ 4 response categories) was sparse, with most cells having expected counts below 5, age was collapsed into three groups (26-30, 31-35, and $\geq$ 36 years) and knowledge into three categories (strongly disagree/neither agree nor disagree, agree, and strongly agree). The association was tested with the Fisher-Freeman-Halton exact test (two-sided), with exact p-values obtained by full enumeration of all tables with the observed margins; Pearson's χ^2 statistic and Cramér's V are reported as descriptive measures of association. As sensitivity analyses, a 3×2 exact test (strongly agree vs. other responses) and Spearman's rank correlation between age (in years) and the ordinal knowledge score were computed. Statistical significance was set at $\alpha = 0.05$. Open-ended responses were analysed thematically using the coding matrix in Table 2, and quantitative and qualitative findings were integrated in a convergent design.

5 Results

This section presents the data gathered from 84 hospital pharmacists employed in healthcare institutions in Rizal Province that had not yet implemented an integrated CDSS. Findings are organized according to the specific objectives: perceived usefulness, willingness to adopt and trust, and perceived barriers, followed by the qualitative themes.

5.1 Item-Level Descriptive Statistics

Table 3 summarizes the means, SEs, and 95% CIs for the 15 Likert items. All five perceived-usefulness items (Q1-Q5) had high means (4.25-4.42). The willingness and trust items (Q6-Q10) had means between 3.76 and 4.13, and the barrier items (Q11-Q15) ranged from moderate (Q12-Q14: 2.99-3.33) to high (Q11: 4.20; Q15: 3.95).

5.2 Age and Self-Reported CDSS Knowledge

Respondents were aged 26-58 years, with the largest single-age group at 30 years ($n = 15$); 68 of 84 respondents (81.0%) were aged 28-35 years. Table 4 cross-tabulates age and self-reported level of CDSS knowledge. After checking against the raw data, the row for age 57 was corrected (the single 57-year-old respondent selected "agree"), and the "strongly agree" column total was corrected to 32; the column totals now sum to $N = 84$. Most respondents agreed (45; 53.6%) or strongly agreed (32; 38.1%) that they were knowledgeable about CDSS, while 4 (4.8%) strongly disagreed, 3 (3.6%) were neutral, and none selected "disagree".

The $p = 0.859$ reported in an earlier version of this manuscript was incorrect. On the full 17×4 table (Table 4, Panel A), Pearson's test gives $\chi^2(48) = 28.62$, $p = 0.988$; however, 64 of 68 cells (94.1%) had expected counts below 5, so the asymptotic χ^2 approximation is not valid and this result is shown for transparency only. After categories were merged (Panel B), the Fisher-Freeman-Halton exact test showed no significant association between age group and self-reported CDSS knowledge ($p = 0.389$;

Table 2. Thematic code matrix for the open-ended questions.

Core research theme	Relevant survey question(s)	Expected sub-themes / qualitative codes
Theme 1: Perceived usefulness and clinical impact	Q1: Main benefits; Q3: Impact on speed or quality	*Error reduction:* medication safety, detection of drug-drug interactions, dosage checks. *Workflow efficiency:* faster prescription validation, optimized clinical interventions, transition from manual to automated processes. *Quality of care:* evidence-based decision support, enhanced clinical confidence.
Theme 2: Systemic, structural, and routine barriers	Q2: Structural/administrative reasons; Q5: Primary routine barriers	*Financial constraints:* software acquisition, licence fees, upgrades. *Technical infrastructure:* lack of integrated hospital information systems, slow hardware, poor IT support. *Administrative inertia:* low prioritization by management, budget allocation. *Workload and time:* alert fatigue, time needed to learn the software.
Theme 3: Willingness to adopt and optimization needs	Q4: Design improvements; Q6: Additional comments/anecdotes	*User-centred design:* simple user interface, integration with existing electronic medical records (EMRs). *Training and readiness:* hospital-wide training, continuous technical orientation. *Acceptance vs. scepticism:* eagerness to transition versus fear of over-reliance on AI.

$\chi^2(4) = 4.32$; Cramér's $V = 0.16$). Even after merging, 4 of 9 cells (44.4%) had expected counts below 5 (minimum 1.00), which is why the exact test was used as the primary analysis. The sensitivity analyses led to the same conclusion: the 3×2 exact test of strongly agree vs. other responses gave $p = 0.258$ ($\chi^2(2) = 2.78$; Cramér's $V = 0.18$), and Spearman's correlation between age and knowledge score was weak and non-significant ($\rho = 0.18$, $p = 0.100$). Given the small number of respondents aged 36 years or older ($n = 12$), these analyses had limited power, and the absence of a significant association should not be interpreted as evidence that knowledge is equivalent across age groups.

5.3 Perceived Usefulness

The response distributions for Q1-Q5 are shown in Tables 5, 6, 7, 8, and 9. As shown in Table 5, for medication error reduction (Q1; mean 4.25), 92.86% agreed (48.81%) or strongly agreed (44.05%) that an integrated CDSS would significantly reduce prescribing and dispensing risks. For drug-drug interactions (Q2; mean 4.36), 91.67% expected a CDSS to improve their speed in identifying complex interactions (Table 6). For overlooked risks (Q3; mean 4.30), 88.10% agreed that automated screening would catch risks missed in manual review (Table 7). For professional efficiency (Q4; mean 4.42), 92.86% agreed or strongly agreed that point-of-care recommendations would increase their efficiency (Table 8); the same proportion (92.86%) considered CDSS necessary for improving institutional patient safety (Q5; mean 4.40; Table 9).

5.4 Willingness to Adopt and Trust Factors

Willingness to adopt AI-driven tools was conditional on explainability, evidence verification, and transparency (Tables 10, 11, 12, 13, and 14). As shown in Table 10, a combined 82.14% would rely on automated recommendations if a clear clinical rationale were provided (Q6). Table 11 shows that 83.33% would trust alerts more if they linked to updated journals or guidelines (Q7), and Table 12 shows that 85.71% would be more willing to use a CDSS that displayed evidence grades (Q8). Likewise, 82.14% agreed that they would trust machine-generated logic only if they could review the calculation pathway (Q10; Table 14). For self-reported alert handling (Q9), 78.57% agreed or strongly agreed that they frequently override alerts to maintain clinical speed (mean 3.76; Table 13). Because none of the respondents' hospitals had implemented an integrated CDSS, these responses do not describe overrides of CDSS alerts. The item did not ask respondents to name the source of the alerts; in this setting, they would most plausibly refer to warnings generated by other electronic tools that pharmacists may use in daily practice (e.g., stand-alone drug-interaction

Table 3. Mean scores of perceptions, trust factors, and implementation barriers regarding CDSS ($N = 84$).

Item / survey question	Mean	SE	95% CI	
			Lower	Upper
Perceived usefulness and patient safety (*Q1-Q5*)				
1. I believe an integrated CDSS would significantly reduce medication errors in my hospital.	4.250	0.106	4.040	4.460
2. I expect that a CDSS would improve my speed in identifying complex drug-drug interactions.	4.357	0.101	4.156	4.558
3. I expect an automated system to catch clinical risks that might be missed during manual reviews.	4.298	0.105	4.088	4.507
4. I believe that evidence-based recommendations at the point of care would increase my professional efficiency.	4.417	0.093	4.232	4.602
5. Overall, I believe implementing a CDSS is necessary for improving patient safety in my institution.	4.405	0.109	4.189	4.621
Willingness to adopt and trust factors (*Q6-Q10*)				
6. I am willing to rely on automated recommendations if the system provides a clear clinical rationale for its alerts.	3.964	0.095	3.775	4.153
7. I would trust a machine-generated alert more if it provided direct links to updated clinical journals or guidelines.	4.036	0.090	3.856	4.215
8. I would be more willing to use a CDSS if it indicated the "level of evidence" (e.g., Grade A vs. Grade C) for its suggestions.	4.131	0.109	3.913	4.349
9. I frequently override alerts to maintain clinical speed.	3.762	0.086	3.591	3.932
10. I trust machine-generated logic only if the system allows me to review the calculation pathway used for the recommendation.	3.988	0.099	3.790	4.186
Perceived barriers to implementation (*Q11-Q15*)				
11. I believe the high cost of software and infrastructure is the main reason our hospital has not implemented a CDSS.	4.202	0.095	4.012	4.392
12. I am concerned that a CDSS would disrupt my current workflow and increase my time spent on a computer.	3.155	0.110	2.935	3.374
13. I worry that a high volume of irrelevant notifications would prevent me from using the system effectively.	3.333	0.114	3.107	3.560
14. In high-pressure or emergency situations, I believe the time required to interact with a computer system will be seen as a hindrance rather than a help.	2.988	0.110	2.768	3.208
15. I am concerned that a lack of technical support and dedicated IT personnel in our hospital would make it difficult to rely on a CDSS for daily clinical decisions.	3.952	0.088	3.778	4.127

Note. SE = standard error; CI = confidence interval. Values are raw (non-reverse-coded) item scores. Respondents strongly agreed on the usefulness of CDSS (Q1-Q5); trust was conditional on visible evidence levels, links to references, and clear rationales (Q6-Q10); and the main barriers were software costs and limited IT support (Q11, Q15), whereas respondents were relatively neutral about workflow disruption, notification burden, and emergency hindrance (Q12-Q14).

checkers, drug-information applications, or pharmacy dispensing and inventory software), to experience gained in other institutions, or to anticipated behaviour. Q9 is therefore interpreted as an indicator of a general self-reported tendency to bypass electronic warnings under time pressure, not as a measured CDSS override rate.

5.5 Perceived Barriers to Implementation

The most prominent perceived impediments were financial and institutional rather than individual (Tables 15, 16, 17, 18, and 19). As shown in Table 15, a combined 86.90% identified high software and infrastructure costs as the main reason for non-implementation (Q11), and Table 19 shows that

Table 4. Contingency table of respondent age and self-reported level of knowledge regarding CDSS.

Panel A. Single-year age by response category

Age (y)	SD	N	A	SA	Total
26	0	0	1	0	1
27	0	0	2	1	3
28	0	0	3	2	5
29	0	1	7	1	9
30	1	1	8	5	15
31	1	1	3	3	8
32	1	0	2	2	5
33	1	0	3	6	10
34	0	0	7	3	10
35	0	0	2	4	6
36	0	0	3	2	5
42	0	0	1	0	1
47	0	0	0	2	2
48	0	0	1	0	1
52	0	0	1	0	1
57	0	0	1	0	1
58	0	0	0	1	1
Total	4	3	45	32	84

Panel B. Merged categories, n (row %)

Age group	SD/N	A	SA	Total
26-30	3 (9.1)	21 (63.6)	9 (27.3)	33
31-35	4 (10.3)	17 (43.6)	18 (46.2)	39
≥ 36	0 (0.0)	7 (58.3)	5 (41.7)	12
Total	7 (8.3)	45 (53.6)	32 (38.1)	84

Note. SD = strongly disagree; N = neither agree nor disagree; A = agree; SA = strongly agree (no respondent selected "disagree"). The age-57 row and the SA column total were corrected against the raw data. Panel A: Pearson $\chi^2(48) = 28.62$, $p = 0.988$; 64/68 cells (94.1%) had expected counts < 5, so this test is not valid and is reported for transparency only. Panel B: Fisher-Freeman-Halton exact test, $p = 0.389$; $\chi^2(4) = 4.32$; Cramér's $V = 0.16$; 4/9 cells had expected counts < 5 (minimum 1.00). Sensitivity analyses: SA vs. other responses, 3×2 exact test, $p = 0.258$; Spearman's $\rho = 0.18$, $p = 0.100$.

82.14% were concerned that insufficient technical support and dedicated IT personnel would limit their reliance on a CDSS (Q15). Concern about workflow disruption and screen time (Q12) was divided: 42.86% were neutral and 34.52% were concerned (Table 16). For irrelevant notifications (Q13), 44.05% agreed that alert fatigue would threaten effective use, while 38.10% were neutral (Table 17). Respondents did not strongly believe that computer interaction would compromise emergency care (Q14; mean 2.99): 38.10% were neutral, and slightly more disagreed (32.14%) than agreed (29.76%) (Table 18).

Table 5. Frequency and percentage distribution of perceived CDSS usefulness in minimizing clinical risks and medication errors (Q1).

Q1. "I believe an integrated CDSS would significantly reduce medication errors in my hospital."

Response	f	%	Cum. %
Strongly disagree	5	5.95	5.95
Disagree	0	0.00	5.95
Neither agree nor disagree	1	1.19	7.14
Agree	41	48.81	55.95
Strongly agree	37	44.05	100.00
Total	84	100.00	

Note. $N = 84$. The distribution is strongly skewed towards agreement: 92.86% of pharmacists agreed or strongly agreed that an integrated CDSS would reduce medication errors.

Table 6. Frequency and percentage distribution of perceived CDSS usefulness in identifying drug-drug interactions efficiently (Q2).

Q2. "I expect that a CDSS would improve my speed in identifying complex drug-drug interactions."

Response	f	%	Cum. %
Strongly disagree	3	3.57	3.57
Disagree	2	2.38	5.95
Neither agree nor disagree	2	2.38	8.33
Agree	32	38.10	46.43
Strongly agree	45	53.57	100.00
Total	84	100.00	

Note. $N = 84$. A combined 91.67% of pharmacists agreed or strongly agreed with this aspect of perceived usefulness.

Table 7. Frequency and percentage distribution of the perceived capacity of an automated system to identify overlooked clinical risks (Q3).

Q3. "I expect an automated system to catch clinical risks that might be missed during manual reviews."

Response	f	%	Cum. %
Strongly disagree	4	4.76	4.76
Disagree	0	0.00	4.76
Neither agree nor disagree	6	7.14	11.90
Agree	31	36.90	48.81
Strongly agree	43	51.19	100.00
Total	84	100.00	

Note. $N = 84$. A combined 88.10% agreed or strongly agreed that automated screening would add protective value to manual review.

5.6 Qualitative Findings

Thematic analysis of the open-ended responses yielded three themes, summarized with illustrative quotations in Tables 20, 21, and 22.

Table 8. Frequency and percentage distribution of the perceived influence of point-of-care decision support on professional efficiency (Q4).

Q4. "I believe that evidence-based recommendations at the point of care would increase my professional efficiency."

Response	*f*	%	Cum. %
Strongly disagree	2	2.38	2.38
Disagree	2	2.38	4.76
Neither agree nor disagree	2	2.38	7.14
Agree	31	36.90	44.05
Strongly agree	47	55.95	100.00
Total	84	100.00	

Note. $N = 84$. A combined 92.86% agreed or strongly agreed that point-of-care recommendations would improve their efficiency.

Table 9. Frequency and percentage distribution of the overall valuation of institutional CDSS adoption for improving patient safety (Q5).

Q5. "Overall, I believe implementing a CDSS is necessary for improving patient safety in my institution."

Response	*f*	%	Cum. %
Strongly disagree	5	5.95	5.95
Disagree	0	0.00	5.95
Neither agree nor disagree	1	1.19	7.14
Agree	28	33.33	40.48
Strongly agree	50	59.52	100.00
Total	84	100.00	

Note. $N = 84$. A combined 92.86% agreed or strongly agreed that adopting a CDSS is necessary for improving institutional patient safety.

Table 10. Frequency and percentage distribution of willingness to rely on automated recommendations accompanied by a clear clinical rationale (Q6).

Q6. "I am willing to rely on automated recommendations if the system provides a clear clinical rationale for its alerts."

Response	*f*	%	Cum. %
Strongly disagree	2	2.38	2.38
Disagree	4	4.76	7.14
Neither agree nor disagree	9	10.71	17.86
Agree	49	58.33	76.19
Strongly agree	20	23.81	100.00
Total	84	100.00	

Note. $N = 84$. A combined 82.14% agreed or strongly agreed that they would rely on automated recommendations if a clear rationale were provided.

Theme 1: Perceived usefulness and clinical impact (Table 20). Respondents viewed CDSS as a vital clinical asset that would compress decision latency

Table 11. Frequency and percentage distribution of trust in machine-generated alerts linked to clinical references (Q7).

Q7. "I would trust a machine-generated alert more if it provided direct links to updated clinical journals or guidelines."

Response	*f*	%	Cum. %
Strongly disagree	1	1.19	1.19
Disagree	4	4.76	5.95
Neither agree nor disagree	9	10.71	16.67
Agree	47	55.95	72.62
Strongly agree	23	27.38	100.00
Total	84	100.00	

Note. $N = 84$. A combined 83.33% agreed or strongly agreed that links to verifiable evidence would increase their trust in alerts.

Table 12. Frequency and percentage distribution of willingness to use a CDSS that displays the level of evidence (Q8).

Q8. "I would be more willing to use a CDSS if it indicated the "level of evidence" (e.g., Grade A vs. Grade C) for its suggestions."

Response	*f*	%	Cum. %
Strongly disagree	5	5.95	5.95
Disagree	0	0.00	5.95
Neither agree nor disagree	7	8.33	14.29
Agree	39	46.43	60.71
Strongly agree	33	39.29	100.00
Total	84	100.00	

Note. $N = 84$. A combined 85.71% agreed or strongly agreed that explicit evidence grading would increase their willingness to use a CDSS.

Table 13. Frequency and percentage distribution of self-reported tendency to override electronic alerts (Q9).

Q9. "I frequently override alerts to maintain clinical speed."

Response	*f*	%	Cum. %
Strongly disagree	4	4.76	4.76
Disagree	0	0.00	4.76
Neither agree nor disagree	14	16.67	21.43
Agree	60	71.43	92.86
Strongly agree	6	7.14	100.00
Total	84	100.00	

Note. $N = 84$. A combined 78.57% agreed or strongly agreed with the statement. The item did not specify the source of the alerts. Because respondents worked in hospitals without an integrated CDSS, responses reflect a general self-reported tendency in handling electronic medication alerts (e.g., from stand-alone drug-interaction checkers, drug-information applications, or dispensing software, or from experience elsewhere) or anticipated behaviour, and are not a CDSS override rate.

Table 14. Frequency and percentage distribution of trust conditional on auditability of the calculation pathway (Q10).

Q10. "I trust machine-generated logic only if the system allows me to review the calculation pathway used for the recommendation."

Response	f	%	Cum. %
Strongly disagree	4	4.76	4.76
Disagree	0	0.00	4.76
Neither agree nor disagree	11	13.10	17.86
Agree	47	55.95	73.81
Strongly agree	22	26.19	100.00
Total	84	100.00	

Note. $N = 84$. A combined 82.14% agreed or strongly agreed that their trust depends on being able to review the underlying calculation pathway.

Table 15. Frequency and percentage distribution of perceived economic and infrastructural barriers (Q11).

Q11. "I believe the high cost of software and infrastructure is the main reason our hospital has not implemented a CDSS."

Response	f	%	Cum. %
Strongly disagree	2	2.38	2.38
Disagree	2	2.38	4.76
Neither agree nor disagree	7	8.33	13.10
Agree	39	46.43	59.52
Strongly agree	34	40.48	100.00
Total	84	100.00	

Note. $N = 84$. A combined 86.90% agreed or strongly agreed that cost is the main reason for non-implementation.

Table 16. Frequency and percentage distribution of concern about workflow disruption and screen time (Q12).

Q12. "I am concerned that a CDSS would disrupt my current workflow and increase my time spent on a computer."

Response	f	%	Cum. %
Strongly disagree	5	5.95	5.95
Disagree	14	16.67	22.62
Neither agree nor disagree	36	42.86	65.48
Agree	21	25.00	90.48
Strongly agree	8	9.52	100.00
Total	84	100.00	

Note. $N = 84$. Opinion was divided: the largest group (42.86%) was neutral, 34.52% expressed concern, and 22.62% disagreed.

Table 17. Frequency and percentage distribution of concern about irrelevant notifications and alert fatigue (Q13).

Q13. "I worry that a high volume of irrelevant notifications would prevent me from using the system effectively."

Response	f	%	Cum. %
Strongly disagree	5	5.95	5.95
Disagree	10	11.90	17.86
Neither agree nor disagree	32	38.10	55.95
Agree	26	30.95	86.90
Strongly agree	11	13.10	100.00
Total	84	100.00	

Note. $N = 84$. A combined 44.05% agreed or strongly agreed that irrelevant notifications would impair effective use, while 38.10% were neutral.

Table 18. Frequency and percentage distribution of perceived hindrance of computer interaction in high-pressure or emergency situations (Q14).

Q14. "In high-pressure or emergency situations, I believe the time required to interact with a computer system will be seen as a hindrance rather than a help."

Response	f	%	Cum. %
Strongly disagree	5	5.95	5.95
Disagree	22	26.19	32.14
Neither agree nor disagree	32	38.10	70.24
Agree	19	22.62	92.86
Strongly agree	6	7.14	100.00
Total	84	100.00	

Note. $N = 84$. The largest group (38.10%) was neutral; slightly more respondents disagreed (32.14%) than agreed (29.76%).

Table 19. Frequency and percentage distribution of concern about technical support and dedicated IT personnel (Q15).

Q15. "I am concerned that a lack of technical support and dedicated IT personnel in our hospital would make it difficult to rely on a CDSS for daily clinical decisions."

Response	f	%	Cum. %
Strongly disagree	2	2.38	2.38
Disagree	2	2.38	4.76
Neither agree nor disagree	11	13.10	17.86
Agree	52	61.90	79.76
Strongly agree	17	20.24	100.00
Total	84	100.00	

Note. $N = 84$. A combined 82.14% agreed or strongly agreed that limited technical support would constrain reliance on a CDSS.

and shift their work from reactive, isolated medication checking to proactive, holistic interception of clinical risks before dispensing. They did not describe digital adoption as an administrative burden but as a mechanism to reduce human verification errors, particularly in high-urgency settings.

Theme 2: Systemic, structural, and routine barriers (Table 21). Respondents described a triad of barriers: institutional inertia of paper-based prescribing;

Table 20. Qualitative Theme 1: perceived usefulness and clinical impact.

Sub-theme / code	Conceptual meaning	Illustrative verbatim quotations
1A: Proactive risk and error interception	Moving from a retroactive model (discovering an error after dispensing) to catching severe clinical risks at initial order entry.	"The primary benefit would be the automation of routine clinical screening… a CDSS can significantly minimize human error by providing real-time alerts for drug-drug interactions…" / "Prevent medication error, correct nurses if they read wrong medication or wrong interpretation." / "It would help me to quickly identify interactions or adverse effects in various medicines I will dispense…"
1B: Multi-dimensional patient view vs. disconnected tasks	Shifting focus from evaluating prescriptions in isolation to assessing the patient's full medical history.	"The quality goes up because the system looks at the patient's entire profile, not just one isolated prescription." / "It will be useful to see the patient's history." / "Compared to the current manual process, it would reduce time spent cross-checking guidelines, renal dose adjustments, drug interactions…"
1C: Compression of decision latency	Minimizing manual workflows and reference-book checks, enabling rapid validation in high-urgency windows.	"Decision making will be faster because answers will be readily available." / "It cuts out the lag time between a doctor writing a bad order and the pharmacy realizing it." / "It helps us answer the ER nurses quickly when they are rushing us for the availability and safety of emergency loading doses."

Table 21. Qualitative Theme 2: systemic, structural, and routine barriers.

Sub-theme / code	Conceptual meaning	Illustrative verbatim quotations
2A: Persistent legacy paper infrastructure	Reliance on paper-based charting and handwritten prescriptions, which makes digital transition difficult.	"Our hospital still relies entirely or primarily on traditional, paper-based charting and handwritten prescription workflows." / "There is a deeply entrenched legacy clinical culture where senior medical staff prefer verbal orders and traditional written prescriptions…" / "The hospital is still paper based."
2B: Strict budget allocation limitations	Municipal or hospital financial frameworks that prioritize immediate medical inventory over long-term digital systems.	"The access to the system itself due to the lack of budget." / "Local Government Unit (LGU) budget limitations restrict provincial funding allocations for advanced healthcare informatics in district hospitals." / "Management always prioritizes buying life-saving meds over upgrading our IT software."
2C: High labour burden and staff shortages	Chronic understaffing that leaves pharmacists no time to learn or navigate new applications.	"We use it manually, but due to lack of staff its hard for us to implement this kind of service." / "Severe shortage of hospital pharmacists to manage daily operations, leaving no time for system training." / "We are chronically understaffed just filling daily prescriptions, leaving zero time to learn a system."

local government unit (LGU) and hospital budget limitations that prioritize immediate medical inventory over software; and chronic understaffing that leaves no time for system training. Introducing a CDSS is therefore unlikely to succeed without addressing staffing and upgrading the underlying EMR infrastructure.

Theme 3: Willingness to adopt and optimization needs (Table 22). Willingness was high but conditional on three design features: minimal user-interface friction ("less clicking"), an "invisible assistant" tiered alerting model that suppresses minor notifications, and preservation of human clinical judgment, with the software acting as a safety net rather than a replacement for professional decision-making.

Table 22. Qualitative Theme 3: willingness to adopt and optimization needs.

Sub-theme / code	Conceptual meaning	Illustrative verbatim quotations
3A: Minimization of UI friction ("less clicking")	Eliminating repetitive manual fields and complex navigation to maximize speed.	"Less clicking for data inputs." / "It should be seamless and less hassle." / "The CDSS could be improved by making the interface more user-friendly, customizable, and well-integrated with existing hospital systems…"
3B: The "invisible assistant"	Software that stays quiet for low-severity issues but actively alerts the clinician to high-severity dangers.	"It should act like an invisible assistant that flags the big issues without adding extra paperwork to our day." / "To prevent adding to our workload, the system must be designed to avoid 'alert fatigue'… only interrupts the workflow for critical, actionable clinical threats." / "The software must sync seamlessly with the doctors' portal so we don't have to re-encode…"
3C: Primacy of human clinical judgment	Refusal to let machine logic replace pharmacists; systems should function only as verification safety nets.	"AI also can make errors, it is better to rely on a true medical or healthcare worker." / "Clinical judgment remains essential because patient-specific factors are often too complex for automated systems alone." / "Our basic or complex knowledge about interactions is quickly replaced by automated AI… it can be optional depending on the pharmacist on duty…"

6 Discussion

The quantitative indicators show that hospital pharmacists in Rizal Province exhibit a high level of conceptual readiness regarding the usefulness of CDSS and its value to patient safety, recognizing its potential to strengthen institutional defences against medication errors. This is consistent with evidence that CDSS improve the process of care and reduce prescribing errors [13, 33].

However, behavioural readiness is contingent on algorithmic transparency and technical infrastructure. Although respondents expressed only moderate concern about disruption during acute situations, they strongly endorsed institutional support deficits as barriers. Because the respondents' hospitals had not implemented a CDSS, the high level of agreement with Q9 does not represent observed CDSS overrides; it reflects a self-reported tendency to bypass electronic warnings from other tools (e.g., stand-alone drug-interaction checkers or dispensing software), experience elsewhere, or anticipated behaviour. Read in this way, it is a warning that a poorly calibrated, non-auditable CDSS that generates excessive notifications could induce the systematic workarounds documented in settings with established CDSS [17, 28]; whether this tendency translates into actual CDSS override rates can only be established after implementation. The demand for rationales, reference links, and evidence grades mirrors what clinicians elsewhere require from explainable systems [16, 38].

When the quantitative and qualitative strands are integrated, an operational paradox emerges: the workforce is conceptually prepared for digital transformation, yet remains structurally constrained by its practice environment. The absence of a significant association between age group and self-reported knowledge (exact $p = 0.389$; Cramér's $V = 0.16$) is consistent with the view that non-adoption is not primarily explained by generational unfamiliarity; however, given the small number of older respondents and the limited power of the test (Table 4), this finding should be regarded as exploratory. The qualitative data point instead to environmental and administrative root causes–paper-based legacy systems, budget priorities, and understaffing–consistent with the organizational barriers reported in hospital CDSS uptake studies [15, 37].

Successful health-informatics integration in Rizal Province therefore cannot be achieved through software procurement alone. Administrators and policymakers would need to address understaffing that leaves clinicians unable to engage with new technology, and system development would need to align with practitioner-defined requirements (Theme 3): streamlined, low-friction interfaces that preserve efficiency and respect pharmacists' final clinical

authority.

7 Conclusion

This study examined the perspectives of 84 hospital pharmacists in Rizal Province on implementing CDSS in non-implementing institutions, across the axes of perceived usefulness, implementation barriers, and willingness to adopt. The results reveal an operational paradox: the local pharmacy workforce expressed strong conceptual readiness and clinical alignment for a technological transition, yet reported being constrained by the administrative and financial conditions of their practice environments.

Respondents spanned 26 to 58 years of age. Self-reported CDSS knowledge was not significantly associated with age group (Fisher-Freeman-Halton exact test, $p = 0.389$), suggesting that barriers to adoption are unlikely to be primarily generational; however, given the sparse contingency table and the concentration of respondents aged 28-35 years, this inference is tentative.

Pharmacists showed strong consensus on the clinical utility of CDSS: 92.86% agreed that it would significantly reduce medication errors, 91.67% anticipated faster identification of drug-drug interactions, 88.10% expected automated systems to catch risks missed in manual review, and 92.86% believed that point-of-care recommendations would improve professional efficiency. This disposition was constrained by institutional bottlenecks: 86.90% identified high software and infrastructure costs as the primary reason for non-implementation, and 82.14% were concerned about insufficient technical support and IT personnel. Concern about routine disruption was comparatively limited (34.52% concerned; 42.86% neutral).

Trust was conditional. A combined 78.57% reported a general tendency to override electronic alerts to maintain clinical speed; because their hospitals had no CDSS, this reflects alerts from other tools or anticipated behaviour rather than CDSS overrides. In addition, 82.14%-85.71% indicated that clear rationales, auditable calculation pathways, links to references, or explicit evidence grades would increase their trust or willingness to use a CDSS. If a platform behaves as a "black box" or generates unstratified, high-volume notifications–a concern shared by 44.05% of respondents–pharmacists may bypass it to preserve their workflow.

Non-implementation of CDSS in Rizal Province therefore appears to be primarily environmental and administrative rather than rooted in professional resistance. Sustainable adoption requires administrators to address technical-support deficits and allocate capital, and developers to design transparent systems that preserve clinical autonomy and support–rather than override–pharmacists' judgment.

7.1 Implications

Theoretical implications. Technology-acceptance frameworks such as TAM and UTAUT have often treated age as a moderator of digital literacy and resistance to change [36]. In this sample, self-reported CDSS knowledge did not differ significantly by age, suggesting that future health-informatics models should give at least equal weight to environmental and structural determinants of acceptance. In addition, although respondents strongly recognized the usefulness of CDSS (88.10%-92.86% across Q1-Q5), their willingness to adopt was conditional on algorithmic transparency, supporting the view that trust in clinical AI must be earned through explainability and auditability [16, 38].

Clinical and practical implications. The most critical practical finding is the high level of agreement with a self-reported tendency to override electronic alerts (78.57%; not a CDSS override rate, because respondents' hospitals had no CDSS), together with concern about irrelevant notifications among 44.05% of respondents. A poorly implemented digital safety system could become a clinical liability: if hospitals procure software with unstratified, "one-size-fits-all" notifications, clinicians may become desensitized and bypass critical safety alerts, undermining the system's protective function [17, 28]. Conversely, an optimized CDSS could shift the pharmacist's role from reactive, post-order validation toward proactive, upstream risk interception by integrating prescribing workflows with laboratory values and other clinical data.

Organizational and administrative implications. Software procurement cannot be treated as a standalone solution to inefficiency or staffing shortages. Because 34.52% of respondents were concerned about workflow disruption and qualitative responses emphasized understaffing, introducing CDSS into high-volume environments without protected training time may increase workload pressure. The finding that 82.14% were concerned about insufficient IT support indicates that hospitals should establish in-house healthcare IT support rather than relying solely on external vendors.

Policy and financial implications. Because 86.90% of respondents identified high procurement costs as the primary institutional hurdle, the findings have direct implications for LGU officials, Department of Health regional offices, and public hospital boards. Policymakers may need to expand definitions of healthcare infrastructure to include clinical informatics; investment in interoperability and CDSS could yield long-term clinical and economic benefits by preventing costly medication errors [34]. These data may also help standardize institutional readiness assessments and guide funding for digital health infrastructure across public and private hospitals.

7.2 Limitations

First, the study was confined to non-implementing hospitals in Rizal Province; the institutional bottlenecks identified are intertwined with local budget allocations and governance structures and may not generalize to highly urbanized centres such as Metro Manila or to low-resource municipalities elsewhere. Second, because only non-implementing facilities were sampled, there was no comparison group of pharmacists working with an active CDSS against which to validate the anticipated barriers. Third, 81.0% of respondents were aged 28-35 years, limiting statistical power for subgroup comparisons involving older practitioners; moreover, even after age groups and response categories were merged, the exploratory age-knowledge analysis had sparse cells and limited power. Fourth, because participants were not interacting with a live CDSS, responses regarding workflow disruption (34.52%) and alert fatigue (44.05%) are predictive rather than observational. Similarly, item Q9 did not specify the source of the alerts being overridden; responses (78.57% agreement) therefore reflect a general self-reported tendency toward electronic alerts from other tools, experience elsewhere, or anticipated behaviour, and cannot be equated with CDSS override rates. Future versions of the instrument should ask respondents to identify the alerting system they are referring to. Fifth, the study was descriptive; associations among perceived usefulness, perceived barriers, trust, and computer literacy were not formally tested. Sixth, self-reported data may be subject to social-desirability and professional-conformity bias, and the instrument measured perceived rather than objectively tested knowledge; the good internal consistency (Cronbach's $\alpha = 0.844$) reflects the coherence of the scale rather than verification of actual informatics competency. Finally, the cross-sectional, non-probability design precludes causal inference. No formal a priori power calculation was conducted, as the study was designed as a census of available pharmacists in non-implementing facilities rather than as an inferential study; future studies should report formal sample-size justifications when testing specific hypotheses.

7.3 Recommendations

For hospital administrations and LGU policymakers. (1) Hospitals should implement a staged operational buffer during rollout, temporarily reducing dispensing quotas and allocating protected, on-the-clock training time, because pharmacists should not be expected to manage high-volume workloads while learning complex systems. (2) Hospital boards should consider modular procurement approaches–such as software-as-a-service (SaaS) or public-private partnerships–that allow incremental implementation, beginning with basic drug-drug interaction alerts and progressively adding laboratory-integrated modules. (3) Hospitals should establish internal healthcare-informatics units, connected to pharmacy operations, to provide real-time support, manage downtime, update formularies, and tune alert sensitivity with clinical staff.

For system and software developers. (1) Developers should avoid opaque "black box" designs; interfaces should display the rationale behind every alert, including the clinical variables used (e.g., creatinine clearance, dose thresholds, and interaction parameters), and link to authoritative guidelines and references. (2) Alerting should be stratified by severity: low-to-moderate-severity warnings should be delivered as passive, non-interruptive inline notifications, whereas only high-severity, life-threatening risks should trigger interruptive alerts requiring documented override justification [17]. (3) Interfaces should minimize clicks so that reviewing, confirming, or safely bypassing a notification requires minimal actions.

For educational institutions and professional associations. Because pharmacists aged 28-35 years form the core of the regional workforce, pharmacy curricula should include applied clinical informatics, EHR navigation, and decision-support concepts, and professional organizations (e.g., the Philippine Pharmacists Association) should develop accredited continuing professional development (CPD) modules on digital health workflows, data privacy, and HCI safety.

For future research. Researchers should (1) conduct longitudinal pre-post evaluations once CDSS is deployed in Rizal Province to test whether anticipated behaviours, such as alert overriding, translate into actual practice; (2) extend sampling to diverse regions of the Philippines, comparing urban and rural settings; and (3) supplement self-reports with objective, simulation-based assessment of pharmacists' interactions with CDSS interfaces, including cognitive workload, error-interception rates, and alert-fatigue thresholds.

Data Availability Statement

Data will be made available on request.

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Conflicts of Interest

The author declares no conflicts of interest.

AI Use Statement

The author declares that ChatGPT-5 was used for language editing, and Perplexity AI was used to assist in formatting bibliographic information; all references were independently verified by the author against the original sources. The author has carefully reviewed, revised, and verified the AI-assisted output and takes full responsibility for the content of the manuscript.

Ethical Approval and Consent to Participate

The study protocol was reviewed and approved by the Philippine Women's University Ethics Review Board (ERB Protocol No. ERB 2020_008; Certificate of Approval dated 12 March 2026). Written informed consent was obtained from all participants before participation. Participation was voluntary, and study data were handled in accordance with applicable Philippine ethical requirements and Republic Act No. 10173 (Data Privacy Act of 2012).

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Appendix

A Survey Questionnaire

Section 1: Demographic information

D1. What is your profession? ☐ Hospital pharmacist ☐ Other (please specify): _____

D2. Age: _____

D3. Gender: _____

D4. How many years have you been in practice? ☐ 1-5 years ☐ 6-10 years ☐ 11-15 years ☐ More than 15 years

D5. What is your level of comfort with digital healthcare technology/AI? 1 (very uncomfortable) 2 (uncomfortable) 3 (neutral) 4 (comfortable) 5 (highly proficient)

Sections 2-4: Likert-scale items. Respondents rated each statement on a 5-point scale: 1 = strongly disagree, 2 = disagree, 3 = neither agree nor disagree ("neutral"), 4 = agree, 5 = strongly agree.

Table A1. Likert-scale items of the survey instrument (Sections 2-4).

No.	Statement
Section 2: Perceived usefulness of CDSS	
Q1	I believe an integrated CDSS would significantly reduce medication errors in my hospital.
Q2	I expect that a CDSS would improve my speed in identifying complex drug-drug interactions.
Q3	I expect an automated system to catch clinical risks that might be missed during manual reviews.
Q4	I believe that evidence-based recommendations at the point of care would increase my professional efficiency.
Q5	Overall, I believe implementing a CDSS is necessary for improving patient safety in my institution.
Section 3: Willingness to use and trust	
Q6	I am willing to rely on automated recommendations if the system provides a clear clinical rationale for its alerts.
Q7	I would trust a machine-generated alert more if it provided direct links to updated clinical journals or guidelines.
Q8	I would be more willing to use a CDSS if it indicated the "level of evidence" (e.g., Grade A vs. Grade C) for its suggestions.
Q9	I frequently override alerts to maintain clinical speed.
Q10	I trust machine-generated logic only if the system allows me to review the calculation pathway used for the recommendation.
Section 4: Barriers to CDSS implementation	
Q11	I believe the high cost of software and infrastructure is the main reason our hospital has not implemented a CDSS.
Q12	I am concerned that a CDSS would disrupt my current workflow and increase my time spent on a computer.
Q13	I worry that a high volume of irrelevant notifications would prevent me from using the system effectively.
Q14	In high-pressure or emergency situations, I believe the time required to interact with a computer system will be seen as a hindrance rather than a help.
Q15	I am concerned that a lack of technical support and dedicated IT personnel in our hospital would make it difficult to rely on a CDSS for daily clinical decisions.

Section 5: Open-ended questions

O1. What are the main benefits of using CDSS in your daily work?

O2. From your perspective as a pharmacist, what is the primary structural or administrative reason your facility has not yet successfully implemented an integrated clinical decision support system?

O3. Beyond catching errors, how do you expect a digital decision-support tool to change the speed or quality of your clinical interventions compared to your current manual process?

O4. How could the CDSS be improved or redesigned to better support your clinical needs without adding to your workload?

O5. What are the primary barriers preventing you from integrating CDSS into your routine?

O6. Any additional comments or personal anecdotes regarding your experience with clinical decision support or AI in healthcare?

B Content Validity Index

Six experts (V1-V6) rated the relevance of each item on a 4-point scale (1 = not relevant to 4 = highly relevant). The I-CVI is the proportion of experts who rated an item 3 or 4 (Table B1).

Table B1. Expert relevance ratings and item-level content validity index (I-CVI).

Item	V1	V2	V3	V4	V5	V6	Rated 3-4	Rated 1-2	I-CVI
Q1	4	4	4	4	4	4	6	0	1.00
Q2	3	3	4	4	4	4	6	0	1.00
Q3	3	4	4	4	4	4	6	0	1.00
Q4	4	4	3	4	4	4	6	0	1.00
Q5	4	4	3	4	4	4	6	0	1.00
Q6	3	4	4	4	4	4	6	0	1.00
Q7	2	4	4	4	4	4	5	1	0.83
Q8	3	4	4	4	4	4	6	0	1.00
Q9	3	3	3	4	4	4	6	0	1.00
Q10	3	4	4	3	3	4	6	0	1.00
Q11	2	4	4	4	4	4	5	1	0.83
Q12	2	3	4	4	4	4	5	1	0.83
Q13	3	3	4	4	4	4	6	0	1.00
Q14	1	3	4	4	4	4	5	1	0.83
Q15	2	4	4	4	4	4	5	1	0.83
O1-O5	4	4	4	4	4	4	6	0	1.00
O6	4	4	3	4	4	4	6	0	1.00

Note. V1-V6 = expert validators (two health-IT specialists and four hospital pharmacists). For the 15 Likert items, S-CVI/Ave = 0.94 and S-CVI/UA = 0.67; for all 21 items, S-CVI/Ave = 0.96. All items met the retention criterion of I-CVI ≥ 0.83 for a six-member panel.

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