Original Article

A Practice Maturity Model for Moving from Digital Tools to Intelligence-Augmented Pharmacy

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Abstract

Digital adoption in pharmacy is frequently inferred from the presence of electronic records, automated dispensing, decision-support alerts, or artificial-intelligence applications. Such indicators describe technological availability but do not establish whether an organization can use intelligence-generating systems safely, effectively, equitably, and accountably. This article proposes an original practice-maturity model for distinguishing digitization from governed intelligence augmentation. Organizational maturity is defined as the sustainable capability to align a bounded medication-use purpose with dependable data, task-appropriate evidence, workflow integration, professional authority, medication-safety controls, equity assessment, governance, workforce competence, and lifecycle learning. The model combines eight maturity domains, five organizational levels, and conjunctive transition gates. The levels progress from Digitized Foundation through Connected Rule-Based Support, Bounded Validated Intelligence, Supervised Workflow Augmentation, and Governed Intelligence Augmentation. Progression is non-compensatory: technical sophistication cannot offset a critical deficiency in data integrity, safety, human authority, equity, or accountability. Each transition therefore requires evidence appropriate to its claim, moving from infrastructure integrity to model assurance, prospective workflow evaluation, demonstrated practice value, and continuing lifecycle oversight. The model is intended for structured organizational self-assessment, comparative research, implementation planning, and identification of evidence gaps rather than numerical ranking or procurement approval. Validation should examine content validity, inter-rater reliability, construct validity, predictive validity, sensitivity to organizational change, and associations with workflow, safety, equity, and implementation outcomes. The framework remains conceptual, context-dependent, and reversible. It does not establish clinical benefit, regulatory conformity, universal applicability, or deployment readiness, but offers a testable architecture for evaluating when digital pharmacy becomes responsibly intelligence-augmented practice.

Keywords: Digital pharmacy, Artificial intelligence, Pharmacy practice, Medication safety, Human–AI collaboration, Clinical decision support

Introduction

Pharmacy organizations increasingly use digital prescribing, electronic medication records, automated supply functions, clinical decision support, remote services, and artificial intelligence. A pharmacy-specific scoping review nevertheless shows that AI applications vary substantially in purpose, setting, method, and degree of practice integration [1]. Counting applications therefore measures adoption activity, not whether an organization can select, evaluate, govern, and sustain them responsibly.

Digital maturity has similarly been reconceptualized as more than an inventory of technologies or a linear progression toward greater computerization [2]. An electronic workflow may remain fragmented, semantically inconsistent, poorly governed, or unable to support a medication decision. Conversely, a technically modest system may be organizationally mature when its purpose, limitations, professional roles, and monitoring obligations are explicit. The relevant unit of analysis is thus not the algorithm alone, but the pharmacy organization's capability to integrate technology into a medication-use system.

Human–AI complementarity provides a further distinction. High-performance healthcare has been framed around

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combining computational capacity with human contextual judgment rather than assuming automatic professional replacement [3]. In pharmacy, augmentation should therefore mean a bounded contribution to information processing, prioritization, prediction, or generation while pharmacists retain defined authority to interpret context, challenge outputs, escalate uncertainty, and make or communicate medication-related decisions.

Clinical decision-support literature identifies possible gains alongside alert fatigue, workflow disruption, data-quality problems, overreliance, and unintended consequences [4]. These risks show why model performance cannot stand as a proxy for practice usefulness or medication safety. Improvement may arise from better data, redesigned workflows, additional staffing, or heightened attention rather than from the AI component alone. Likewise, continued use may reflect institutional dependence rather than demonstrated benefit.

This article proposes a non-empirical practice-maturity model that links technological capability to evidence, workflow, safety, equity, governance, and workforce conditions. It does not rank products or prescribe a universal implementation sequence. Its purpose is to make advancement claims contestable: an organization should be considered more mature only when it can demonstrate the additional obligations attached to a higher level and can regress when those conditions no longer hold.

Defining Organizational Maturity in Pharmacy AI

Organizational maturity is proposed here as the sustainable capability to use digital and AI systems for bounded medication-use purposes while maintaining adequate data, evidence, workflow design, safety controls, equity assessment, professional authority, governance, and lifecycle learning. Systematic synthesis of hospital digital-maturity dimensions supports treating maturity as multidimensional rather than purely technological [5]. The definition therefore separates infrastructure possession from the organizational capacity to produce defensible practice consequences.

Maturity also differs from initial adoption. Technologies may be accepted yet later abandoned, fail to scale, or prove difficult to sustain because value, users, organizational arrangements, wider systems, or adaptation over time were insufficiently addressed [6]. A maturity designation must consequently reflect durability and change-management capacity, not implementation date.

Organizational AI-readiness research identifies strategic alignment, resources, knowledge, culture, and data as interacting prerequisites [7]. Implementation outcomes are additionally shaped by intervention characteristics, internal and external settings, individuals, and implementation processes [8]. Drawing on these established relationships, this article proposes four connected elements: eight cross-cutting domains, five qualitatively different maturity levels, evidence gates between levels, and a non-compensatory rule for critical failures. The synthesis is pharmacy-specific and requires empirical validation.

Figure 1 presents the original conceptual synthesis for practice maturity model from digitization to governed intelligence augmentation, showing how the article's principal components, evidence relationships, uncertainties, and decision boundaries are connected.

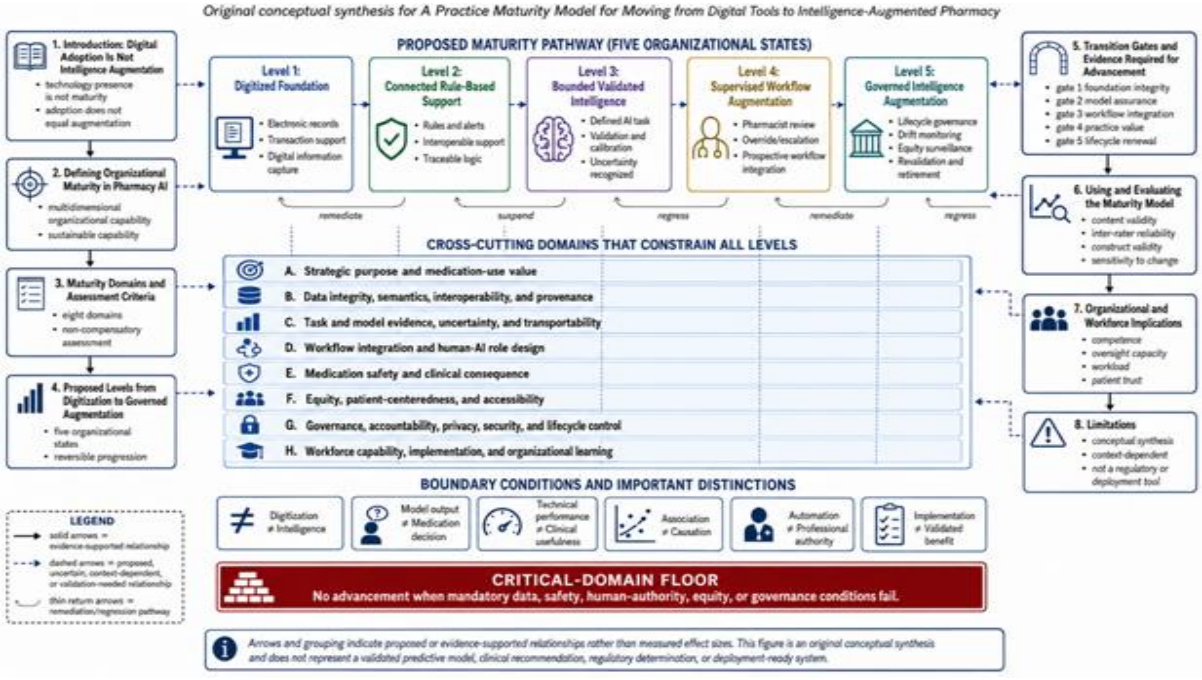

Figure 1. Practice Maturity Model from Digitization to Governed Intelligence Augmentation

The model distinguishes related constructs. Digitization converts information and transactions into electronic form. Digital pharmacy comprises digitally mediated pharmacy services and medication-use processes. Clinical decision support provides task-specific information through rules, knowledge bases, statistical methods, or AI. Artificial intelligence infers, classifies, ranks, predicts, recommends, or generates outputs from data. Intelligence augmentation exists only when those outputs are embedded in an arrangement that preserves contextual review, challenge, escalation, and accountable professional action. Practice maturity is the organizational capability to maintain that arrangement under routine use and change.

Table 1 organizes the evidence, constructs, relationships, uncertainties, and boundary conditions required for definitions, components, relationships, and intended uses for the article A Practice Maturity Model for Moving from Digital Tools to Intelligence-Augmented Pharmacy.

Table 1. Definitions, components, relationships, and intended uses for the article A Practice Maturity Model for Moving from Digital Tools to Intelligence-Augmented Pharmacy

Component or scientific dimension	Problem addressed	Inputs or determinants	Proposed mechanism or relationship	Expected contribution	Evidence required	Failure or uncertainty risk	Boundary statement
Digitized foundation	Paper-to-electronic transition may be mistaken for intelligence	Reliable records, semantics, access, interoperability	Proposed: dependable digital information enables later support	Traceable information flow	Data completeness and workflow verification	Fragmented, delayed, or stale data	Digitization is not intelligence
Digital pharmacy	Technology counts obscure practice purpose [1]	Service model, medication-use task, users	Proposed: tools are assessed through a bounded pharmacy function	Practice-relevant assessment	Task and context description	Technology-led adoption	Digital delivery does not establish benefit
Organizational maturity	Single technical metrics omit organizational capability [5]	Strategy, resources, culture, data, governance	Proposed: eight domains form an integrated capability	Multidimensional assessment	Content and construct validation	False precision from simple scoring	Maturity is not technology volume
Implementation durability	Adoption may not persist or scale [6]	Value, adopters, organization, wider system, adaptation	Maturity requires sustained capability	Distinguishes launch from institutional capacity	Longitudinal implementation evidence	Abandonment or workarounds	Adoption is not sustainability
AI readiness	Technical access may exceed organizational readiness [7]	Strategic alignment, knowledge, resources, culture, data	Readiness conditions enable bounded AI use	Identifies prerequisites	Organizational assessment	Procurement without capability	Readiness is not clinical usefulness
Context and process	Outcomes depend on setting and implementation [8]	Inner setting, outer setting, individuals, process	Context modifies use and sustainability	Supports local interpretation	Multilevel implementation evidence	Unexamined contextual transfer	Local use is not universal applicability
Human–AI augmentation	Automation may obscure professional authority [3]	Role allocation, review, override, escalation	Proposed: complementary decision arrangement preserves professional control	Context-sensitive interpretation	Human-factors and workflow evaluation	Overreliance or nominal oversight	Model output is not medication decision
Governed lifecycle	One-time approval cannot address later change	Accountability, monitoring, change control, retirement	Proposed: maturity creates a continuing evidence obligation	Reversible maturity designation	Prospective monitoring and revalidation	Drift, unmanaged updates, accountability gaps	Implementation is not validated benefit

Maturity Domains and Assessment Criteria

The proposed model contains eight domains that must be assessed together. First, strategic purpose and medication-use value require a defined problem, intended user, beneficiary, baseline pathway, comparator, and explicit non-goals. Second, data integrity, semantics, interoperability, and provenance concern whether inputs are complete, timely, traceable, representative, and meaningful across systems. Third, task and model evidence addresses intended use, validation, calibration where relevant, uncertainty, subgroup performance, and transportability. The clinical-AI literature indicates that movement from promising performance to clinical impact is impeded by data, evaluation, workflow, regulatory, and implementation challenges [9].

Fourth, workflow integration and human–AI role design specify where an output appears, what information accompanies it, who reviews it, and how disagreement,

abstention, escalation, override, and fallback operate. Fifth, medication safety and clinical consequence require hazard analysis, false-positive and false-negative consequence assessment, incident learning, and recovery testing. Responsible machine-learning guidance supports treating harm prevention as a lifecycle obligation extending beyond model development [10].

Sixth, equity, patient-centeredness, and accessibility examine whether data, outputs, access, communication, workload, and downstream intervention burdens differ across relevant populations or settings. Seventh, governance, accountability, privacy, security, and lifecycle control allocate ownership, audit rights, stop authority, vendor obligations, incident response, change control, revalidation, and retirement. Eighth, workforce capability, implementation, and organizational learning address competence, protected review time, psychological safety, feedback, adaptation, and sustained resources.

Explainability is a sociotechnical requirement, but current post-hoc methods do not by themselves establish clinically trustworthy use [11, 12]. Accordingly, explanation quality is assessed within the workflow and governance domains rather than treated as an independent certificate of maturity. The useful question is whether information supplied with an output enables the responsible actor to identify relevance, uncertainty, limitations, and an appropriate response.

Assessment is proposed as criterion-based rather than additive. Each domain contains observable requirements, evidence expectations, critical failure conditions, and an accountable owner. Averages are inappropriate because high performance in one domain could conceal a material deficiency in another. Data integrity, task applicability, medication safety, effective human authority, equity, and governance therefore form a critical-domain floor. Failure of any applicable hard-stop criterion prevents advancement until remediation occurs.

Criteria must remain proportional to risk and intended use. A low-consequence administrative prioritization tool should not automatically face the same evidence burden as a system influencing high-risk medication review. Proportionality, however, does not permit vague intended use or absent accountability. The model asks what evidence is sufficient for the specific claim being made, not whether every system has completed an identical checklist.

Proposed Levels from Digitization to Governed Augmentation

The five proposed levels describe qualitatively different organizational states. They are not technology generations, and an organization may occupy different levels for different tasks. The lowest defensible level for a given use is determined by the least mature mandatory domain, not by the most sophisticated component.

Level 1: Digitized Foundation. This level denotes reliable electronic representation, storage, transmission, and retrieval of medication information and transactions. Electronic prescribing, dispensing records, inventory functions, and digital communication may be present. The level makes no claim that the organization performs computational inference or improves decisions.

Level 2: Connected Rule-Based Support. This level adds interoperable and traceable rules, knowledge-based checks, alerts, or workflow prompts. The organization can identify the origin and logic of the support and assess data quality, routing, and alert burden. This level remains distinct from AI because fixed decision logic does not require learned inference.

Level 3: Bounded Validated Intelligence. This level applies when an AI-enabled component performs a clearly specified task for a defined population, setting, workflow location, and decision boundary. A machine-learning system that identifies prescriptions at elevated risk of medication error illustrates the type of bounded task that may be evaluated at this level [13]. Classification nevertheless requires evidence appropriate to the intended use; a promising retrospective result alone is insufficient.

Level 4: Supervised Workflow Augmentation. This level requires prospective integration with explicit pharmacist authority, usable review, escalation, abstention, override, and fallback pathways. A hybrid medication-review system illustrates how AI may rule out selected prescriptions while retaining pharmacist involvement in the overall process [14]. This evidence supports the feasibility of a hybrid arrangement in its examined context, not the universal validity of the proposed level. Research on AI optimization of medication alerts further indicates potential value alongside heterogeneous methods and limited evaluation evidence [15]. Level 4 therefore depends on observed workflow behavior and unintended consequences, not only reduced alert counts or model accuracy.

Level 5: Governed Intelligence Augmentation. This level denotes an organizational capability to govern a portfolio of intelligence-augmented functions across their lifecycles. Requirements include accountable decision rights, comparative practice evaluation, subgroup and equity surveillance, incident response, drift monitoring, change control, revalidation, workforce renewal, and retirement capacity. Comparative claims require particular caution because reviews of AI-versus-clinician studies have identified limitations in design, reporting, external validation, and interpretation [16]. The highest level consequently represents continuing evidence obligations rather than a permanent achievement.

Progression is conditional and reversible. A system may remain at Level 3 when technical evidence is adequate but workflow authority is unresolved, or regress from Level 5

after a material data, model, vendor, population, staffing, or policy change. The model therefore recognizes maturity as maintained organizational performance under change, not a badge awarded at deployment.

Transition Gates and Evidence Required for Advancement

Advancement is proposed as a sequence of conjunctive evidence gates rather than automatic movement toward more complex technology. Gate 1, Foundation Integrity, requires dependable records, medication semantics, provenance, access control, and a mapped baseline workflow before connected support is introduced. Gate 2, Bounded Model Assurance, requires an explicit intended use, comparator, internal and external validation, calibration where applicable, uncertainty characterization, subgroup assessment, and failure analysis before an AI-enabled task can be classified as bounded validated intelligence.

Advancement to live clinical use requires both early-stage human-factors evaluation and trial-level reporting discipline [17, 18]. Accordingly, Gate 3, Human-Supervised Workflow Integration, examines prospective use, usability, pharmacist authority, override, escalation, abstention, fallback, alert burden, and recovery from failure. Gate 4, Prospective Practice Value, asks whether the complete sociotechnical intervention produces acceptable medication-safety, workflow, equity, resource, and implementation consequences rather than merely favorable model metrics.

Explicit governance is required because responsible use depends on allocated authority, transparency, accountability, and oversight across design and deployment [19]. Gate 5, Lifecycle Renewal, therefore requires continuing incident surveillance, drift and subgroup monitoring, data-change detection, controlled updates, revalidation, audit, and retirement capacity. Trustworthy healthcare AI guidance likewise treats deployability as dependent on fairness, universality, traceability, usability, robustness, and explainability across the lifecycle [20]. Every gate may produce advance, hold, remediate, or regress. Passing one gate establishes only the bounded claim attached to that gate.

Using and Evaluating the Maturity Model

Use should begin with a specific medication-use task, not an organization-wide self-label. Independent assessors should identify the intended level, examine each mandatory domain, document evidence gaps, and assign the highest level for which all applicable criteria are satisfied. TRIPOD+AI supports complete reporting of prediction-model development and evaluation [21], while PROBAST+AI provides structured appraisal of risk of bias and applicability [22]. These tools inform evidence review but do not themselves determine organizational maturity.

Evaluation should address transparency, replicability, ethics, effectiveness, and phase-appropriate quality criteria [23, 24]. Initial validation should test content validity with pharmacists, patients, safety specialists, informaticians, implementation researchers, and organizational leaders. Subsequent studies should examine inter-rater reliability, construct validity, sensitivity to change, and whether higher classifications predict safer integration, more appropriate reliance, sustainable use, and earlier detection of deterioration. Comparisons should retain domain profiles rather than collapse maturity into an unqualified total score.

Organizational and Workforce Implications

Intelligence augmentation changes work allocation, professional identity, and accountability. Patient resistance may increase when AI is perceived as unable to account for individual uniqueness [25]. Organizations therefore need communication and review processes that make the pharmacist's continuing interpretive role visible.

Pharmacy students report substantial interest in AI alongside educational needs, indicating that workforce preparation should include critical appraisal, limitations, ethics, and practical use rather than tool operation alone [26]. Pharmacists' emerging use of AI chatbots similarly creates needs for guidance on verification, confidentiality, reliability, and appropriate task boundaries [27]. Competence must be accompanied by time, authority, escalation routes, and psychological safety to challenge outputs.

Table 2 organizes the evidence, constructs, relationships, uncertainties, and boundary conditions required for governance responsibilities, implementation conditions, and monitoring requirements for the article A Practice Maturity Model for Moving from Digital Tools to Intelligence-Augmented Pharmacy.

Table 2. Governance responsibilities, implementation conditions, and monitoring requirements for the article A Practice Maturity Model for Moving from Digital Tools to Intelligence-Augmented Pharmacy

Governance domain	Responsible actor	Required authority	Documentation requirement	Monitoring indicator	Escalation trigger	Corrective action	Accountability boundary
Purpose and value	Clinical–executive owner	Approve or stop intended use	Proposed: purpose, comparator, and non-goals	Task relevance and workflow consequence	Use outside scope	Restrict or redesign	Adoption does not prove value
Data stewardship	Data and pharmacy owners	Correct, restrict, or	Proposed: provenance, semantics, access, and changes	Missingness, representativeness, and drift	Material input change	Repair, revalidate, or suspend	Data availability does not establish suitability

		suspend data flows					
Model assurance	Model owner and independent evaluator	Reject unsupported claims	Validation, uncertainty, and subgroup findings [21]	Calibration and applicability	Performance deterioration	Recalibrate, constrain, or withdraw	Performance does not establish usefulness
Workflow safety	Pharmacy and safety leads	Define override, escalation, and fallback	Roles, hazards, and incidents	Alert burden and unsafe reliance [17]	Failed review or recovery	Redesign workflow or regress	Oversight without capacity is not control
Equity	Equity lead with patient input	Require subgroup mitigation	Proposed: access, burden, and subgroup assessment	Differential errors or access	Material unequal effect	Mitigate, restrict, or suspend	Aggregate benefit does not establish equity
Lifecycle governance	Accountable oversight body	Audit, halt, update, or retire	Decisions, changes, and incidents [19]	Drift, updates, and unresolved incidents	Unreviewed change or recurring harm	Revalidate, regress, or retire	Deployment is not continuing readiness
Workforce capability	Pharmacy leadership and educators	Set competence and workload conditions	Training, supervision, and feedback [26]	Competence gaps and workarounds	Staff cannot challenge output	Train, resource, or suspend	Training alone does not transfer responsibility

All responsibilities, triggers, corrective actions, and boundaries in **Table 2** are proposed governance specifications; cited sources support the corresponding evidence premise rather than validation of the table.

Limitations

The model is a conceptual synthesis and has not been tested as a measurement instrument. Proxy targets can reproduce inequity despite apparently successful aggregate performance [28], and models may generalize poorly across institutions [29]. Maturity classification must therefore remain task-, population-, workflow-, and setting-specific. Ethical accountability also cannot be transferred to an algorithm merely because its operation is technically sophisticated [30]. Self-assessment may be distorted by optimism, procurement incentives, incomplete incident reporting, or unequal stakeholder power. The framework does not define regulatory compliance, accreditation, procurement eligibility, clinical effectiveness, or permanent readiness.

Conclusion

This article proposes a practice-maturity model that distinguishes digital presence from organizational capability for intelligence augmentation. Its eight domains connect purpose, data, task evidence, workflow authority, medication safety, equity, governance, and workforce learning. Five levels describe increasingly demanding organizational states, while conjunctive gates prevent technical sophistication from compensating for critical weaknesses.

The principal contribution is a reversible, evidence-bounded architecture for asking what an organization can justify, not merely what technology it possesses. It preserves pharmacists' contextual and professional authority while making that authority operational through review capacity, escalation, fallback, and accountability. The model also treats safety, equity, implementation, and lifecycle monitoring as constitutive features of maturity rather than later additions. Empirical work is required to validate its content, measurement properties, decision rules, and relationship to practice outcomes. Until then, it should be used as a structured hypothesis and assessment framework, not as a clinical recommendation, regulatory determination, universal standard, or deployment authorization.

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