Co-Intelligence vs. Human-in-the-Loop

Many healthcare AI systems describe themselves as "human-in-the-loop," but this model often assumes that AI acts first and humans correct later. In nursing care, that sequencing is backwards. By the time a human is asked to intervene, the AI has already shaped the interaction, the patient's expectations, or the clinical trajectory.

Co-intelligence reverses this logic. Humans do not supervise AI after the fact; they govern how, when, and whether AI acts. In safety-critical care, that distinction is not academic—it is the difference between oversight and control.

Healthcare Doesn't Need Smarter AI. It needs Nursing First Co-Intelligence:

Designing Human-Governed AI for Real Care Teams

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Contents

Other Nursing First Articles: Link

- Nursing First GenAI, Agentic AI, &AI: Meet Eddie, Emma, Otto, & Seer
- Nursing First GenAI, Agentic AI, & AI: Assessments and Reassessments
- Nursing First GenAI & AI: Foundation, Safety & Effectiveness
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- Virtual Nursing: Shift & Augment Tasks
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- Virtual Nursing: Beyond Virtual Nursing 1.0
- Virtual Nursing: Early Wins
- Virtual Nursing Aligned to Command Centers
- Virtual Nursing: Lessons Learned

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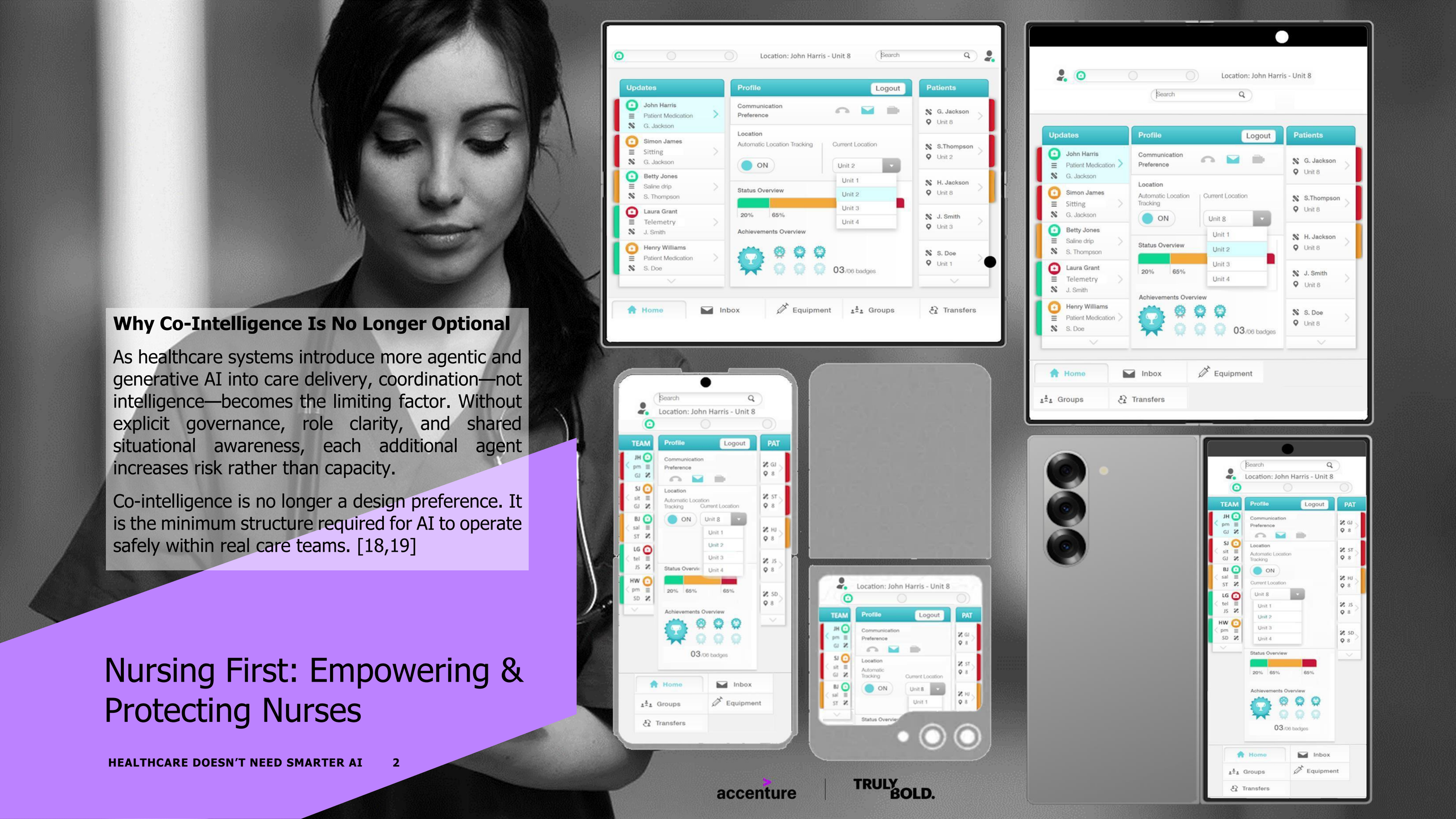

Why Co-Intelligence Is No Longer Optional

As healthcare systems introduce more agentic and generative AI into care delivery, coordination—not intelligence—becomes the limiting factor. Without explicit governance, role clarity, and shared situational awareness, each additional agent increases risk rather than capacity.

Co-intelligence is no longer a design preference. It is the minimum structure required for AI to operate safely within real care teams. [18,19]

Nursing First: Empowering & Protecting Nurses

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Nursing First is the journey to new care models, achieving consistent excellence in care delivery while supporting and building trust and resilience among the nation's most prominent and most trusted professionals in healthcare -- Nurses. Earlier Nursing First articles describe the foundation on which AI and GenAI are helpful to achieving the Nursing First Mindset. First, Nursing First reinvents the care model to empower nurses to achieve better outcomes by leveraging virtual nursing, automation, and technology augmentation, as well as team-based staffing and provider consultations. Second, MyAction Hub is a capability that enables safety, coordination, and communication. Third, automation/augmentation continues to explore the use of AI and GenAI, particularly AI agents or digital humans responsible for aspects of nursing activities.

Nursing First's foundational capabilities:

1

Nursing First Mindset:

Nursing First aims to support nurses in practicing at the top of their license through a nurse-led care delivery model redesign, which fundamentally and sustainably addresses the challenges faced across the nursing profession[1,2,3,4] while embracing applicable technologies. This approach directly involves nurses in creating new ways of working, thereby empowering them to operate in a professionally safe and supportive environment, elevating the patient care experience, and driving the policy and behavioral changes needed for continuous improvement.

2

MyAction Hub: Safety, Effectiveness & Co-Intelligence:

Nursing First's MyAction Hub enables safety, coordination, and communication among the care team. Team care is at the heart of most care models. AI agents should utilize the information known across the care team's use of MyAction Hub to ensure safety and adequate care. Specifically, an AI agent should be able to escalate care to a care team member who is available and within the patient's proximity. At times, an AI agent may redirect responsibilities for a patient to a nurse in the care setting who is closer and more readily available. Moving forward, it will be essential to support co-intelligence and collaboration with the new care team members.

3

Understanding & Deconstructing:

At the core of Nursing First is empowering nurses through the recognition of the broad number of tasks that make up a routine day. Accenture has identified forty (40) activities that are common to nursing, with a particular focus on inpatient, acute nursing.

The goal of Nursing First is to break down each of the 40 identified nursing activities into tasks and subtasks. Then, reinvent workflows by using the four levers of virtual nursing — automation/AI/GenAI, team support, and remote consultations—to perform the task or subtask.

False Safety & Latent Risk

The most dangerous failure mode in healthcare AI is not incorrect answers—it is false safety. When AI appears responsive, empathetic, or confident without being connected to real staffing capacity or escalation pathways, patients believe they are being cared for when they are not. Nurses, in turn, inherit the downstream risk when those assumptions break.

Co-intelligence exists to prevent this failure mode. It ensures that AI never gives patients or care teams a sense of safety that the system cannot deliver.

Nursing First Co-Intelligence: *Designing Human-Governed AI for Real Care Teams*

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Nursing First Co-Intelligence

The current race toward "agentic" and autonomous AI in healthcare assumes that greater intelligence, automation, and independence will naturally lead to better care. For nursing teams, the opposite is often true. Care delivery is not a linear workflow—it is a continuous process of assessment, interruption, escalation, coordination, and human judgment [20,21]. When AI is introduced without respecting those realities, it fragments care, increases cognitive burden, and introduces new safety risks [4,5,13,14,22].

Co-intelligence offers a different path. Rather than asking what AI can do on its own, a Nursing-First approach asks how humans and AI can think, act, and recover together—while preserving human authority, physical presence, and accountability. In nursing care, trust is not built by autonomy. It is built through coordination.

False Safety & Latent Risk

The most dangerous failure mode in healthcare AI is not incorrect answers—it is **false safety**. When AI appears responsive, empathetic, or confident without being connected to real staffing capacity or escalation pathways, patients believe they are being cared for when they are not. Nurses, in turn, inherit the downstream risk when those assumptions break.

This phenomenon aligns with research on automation-induced complacency, in which users develop misplaced trust in automated systems that appear competent but lack proper situational awareness [23,24]. In healthcare specifically, studies have documented cases where patients delayed seeking appropriate care because virtual health tools provided reassurance without adequate clinical oversight [25,26].

Co-intelligence exists to prevent this failure mode. It ensures that AI never gives patients or care teams a sense of safety that the system cannot deliver. This principle draws on resilience engineering concepts that emphasize maintaining awareness of system capacity and explicit failure boundaries [27,28].

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1. The Problem with How AI is Framed in Healthcare Today

Much of today's AI discourse assumes that intelligence equals independence. Many systems are designed to operate autonomously, generating recommendations or actions with limited regard for workflow, accountability, or recovery when things go wrong.

In healthcare, this assumption quickly breaks down. Care delivery is a sociotechnical system involving patients, clinicians, physical environments, policies, and real-time capacity constraints [29,30]. Research consistently shows that AI introduced without strong governance and coordination often increases cognitive load and introduces new failure modes rather than reducing them [4,5,13,14,31].

Studies of clinical decision support systems demonstrate that automation can disrupt nursing workflow through poorly timed alerts, poor integration with existing tools, and insufficient consideration of task-interruption patterns [20,32,33]. Nurses experience an average of 11.5 interruptions per hour during medication administration alone [34], underscoring the critical role of workflow integration in safety and effectiveness.

For nursing teams, the risk is especially acute. Assessments, escalations, and interventions must align with physical presence, shared responsibility, and clear handoffs. This requires a fundamentally different design approach grounded in principles of distributed cognition [35,36].

2. What Co-Intelligence Means in a Nursing First Care Model

Co-intelligence is not autonomy. It is not delegation without oversight. And it is not AI acting independently of human judgment.

In a Nursing First care model, **co-intelligence refers to a distributed cognitive system** characterized by five essential properties:

Defining Properties of Co-Intelligence:

1. **Human-Governed Activation**: AI agents are invoked intentionally by authorized clinicians rather than activating autonomously. This preserves professional judgment and reduces automation bias [23,37].
2. **Capacity-Aware Operation**: AI does not initiate patient-facing interactions unless the system confirms that qualified human responders are available and physically accessible for escalation. This prevents the "false safety" failure mode documented in telehealth studies [25,26].
3. **Explicit Role Boundaries**: Each AI agent performs bounded, well-defined functions with apparent limitations. Agents do not autonomously expand their roles or chain to other agents without human authorization [38,39].
4. **Recoverable Workflows**: The system is designed for interruption, pause, and resumption as regular operation rather than failure states. This aligns with research on interruption management in nursing workflows [20, 32, 34].
5. **Distributed Cognition Architecture**: Intelligence emerges from coordinated interaction among multiple specialized agents and human team members, rather than concentrating cognitive load in a single autonomous system [35,36,40].

These properties operate concepts from several research domains:

- **Distributed cognition theory** [35,36]: Intelligence resides in the coordination among agents, not in individual components
- **Common ground theory** [41,42]: Shared context and mutual knowledge enable effective collaboration
- **High reliability organization principles** [18,19]: Prospective governance and explicit failure boundaries enhance safety
- **Resilience engineering** [27,28]: Systems should degrade gracefully and maintain recovery capacity

This framework shifts the question from "What can AI do on its own?" to "How do humans and AI think and act together safely?"

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2. What Co-Intelligence Means in a Nursing First Care Model

Governance and Managing Change

To ensure that the Nursing First model delivers sustainable impact, robust governance and proactive change management must be embedded from the outset. Research on healthcare technology adoption shows that engaging nursing leadership and frontline staff in the redesign process not only builds trust but also establishes clear accountability for new workflows and technology adoption [43,44,45].

Structured governance frameworks help maintain alignment with clinical standards, while change management strategies—such as ongoing training, transparent communication, and feedback loops—support nurses as they transition to empowered, technology-augmented roles [46,47].

Evidence-Based Measures

Potential Measure	Illustrative Instrument/Method	Illustrative Target Statement	Potential Evidence Base
Nurse Engagement Score	Utrecht Work Engagement Scale (UWES-9) [48]	≥4.0/6.0	Validated across healthcare settings
Practice at the Top of the License	Time-motion study methodology [49,50]	≥70% clinical time	Benchmark from workflow studies
Retention Rate	Annual turnover vs. benchmark [51]	<15% annually	National nursing turnover data
Incident Reports	AHRQ Common Formats [52]	<5 per 1,000 patient days	Patient safety benchmarks
Cognitive Load	NASA Task Load Index (NASA-TLX) [53]	<50/100	Human factors standard
Technology Acceptance	Technology Acceptance Model 3 [54]	≥3.5/5.0	Validated for healthcare IT

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3. Why Healthcare—and Nursing in Particular—Requires a Different AI Model

Healthcare operates under constraints that most AI systems are not designed to handle:

- **Emergencies are unpredictable**: Care cannot wait for AI processing or optimal conditions [55]
- **Physical presence is sometimes mandatory**: Remote oversight cannot substitute for hands-on assessment in many clinical situations [56,57]
- **Responsibility is distributed across roles**: Accountability must be explicitly assigned and traceable [58,59]
- **Interruptions and handoffs are routine**: Nurses experience numerous interruptions per hour on average [34], requiring interruption-resilient design
- **Partial information is common**: Clinical decisions often occur under uncertainty with incomplete data [60,61]

Industry data shows that while most health systems are piloting generative AI, far fewer have addressed the operational and governance requirements needed to support safe deployment [5]. A 2024 survey found that only 23% of healthcare organizations have established AI governance frameworks, despite 67% actively piloting AI solutions [5].

In nursing workflows, intelligence must be situational, interruptible, and recoverable. Time-motion studies demonstrate that nursing tasks are characterized by frequent task switching (average duration of 2-3 minutes per task) and high rates of interruption [49,50,62]. Any AI interacting with patients must know not just what to do, but when it cannot act alone.

Distributed cognition research emphasizes that intelligence in complex systems emerges from coordination among agents rather than individual capability [35,36]. Studies of healthcare teams show that effective coordination reduces errors and improves outcomes more reliably than individual expertise alone [63,64,65].

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3. Why Healthcare—and Nursing in Particular—Requires a Different AI Model

Governance and Managing Change

Effective governance is essential for systems like MyAction Hub to function as a reliable backbone for team coordination and patient safety. Research on clinical information systems shows that governance mechanisms, including escalation protocols, ownership rules, and data stewardship policies, significantly impact system effectiveness and user adoption [66,67].

By explicitly defining these structures, organizations can use capabilities like MyAction Hub to ensure that AI supports safe, compliant, and transparent care delivery. Change management initiatives, including stakeholder engagement and iterative rollout, help teams adapt to new digital workflows and reinforce a culture of shared responsibility and continuous improvement [43,44,46,47].

Evidence-Based Measures

Potential Measure	Illustrative Instrument/Method	Illustrative Target Statement	Potential Evidence Base
Escalation Response Time	Median time from alert to intervention [68]	<5 minutes	ED escalation benchmarks
Task Completion Visibility	Process mining analysis [69]	≥95% tasks visible	Workflow transparency studies
Missed Handoffs	I-PASS handoff assessment [70]	<2 per 100 handoffs	Standardized handoff protocols
Coordination Quality	Collaboration and Satisfaction About Care Decisions (CSACD) [71]	≥4.0/5.0	Team collaboration measurement
Safety Event Rate	AHRQ Common Formats [52]	<3 per 1,000 days	National benchmarks
Shared Mental Model	Team Mental Model accuracy [72]	≥80% concordance	Team cognition research

4. Five Forms of Co-Intelligence in a Real Care Team

In practice, co-intelligence does not appear as a single feature or agent. It emerges through multiple, reinforcing forms of coordination between humans, AI agents, and systems. This framework is grounded in distributed cognition theory [35,36], which posits that intelligence emerges from coordinated interaction rather than individual capability.

Framework Development

The five forms presented here synthesize principles from:

1. **Capacity Awareness:** Distributed cognition and coordination science [35,36,40,73]
2. **Responsibility Surfaces:** High reliability organization theory [18,19,74]
3. **Human-Initiated Delegation:** Human-automation interaction research [23,37,75]
4. **Structured Team Interaction.** Clinical workflow and interruption studies [20,32,34,49,50]
5. **Agent Ecology:** Resilience engineering [27,28,76]

Each form addresses a specific coordination challenge documented in healthcare AI implementation research [4,5,13,14,31,77].

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4.1 Co-Intelligence Through Capacity Awareness

Principle: AI should not act unless the system can respond.

Theoretical Foundation

This principle operates on concepts from:

- **Resilience engineering** [27,28]: Systems must maintain explicit awarene their response capacity
- **HRO theory** [18,19]: High-reliability organizations continuously monitor capacity constraints
- **Automation design principles** [75,78]: Automated systems should not promise capabilities beyond actual system capacity

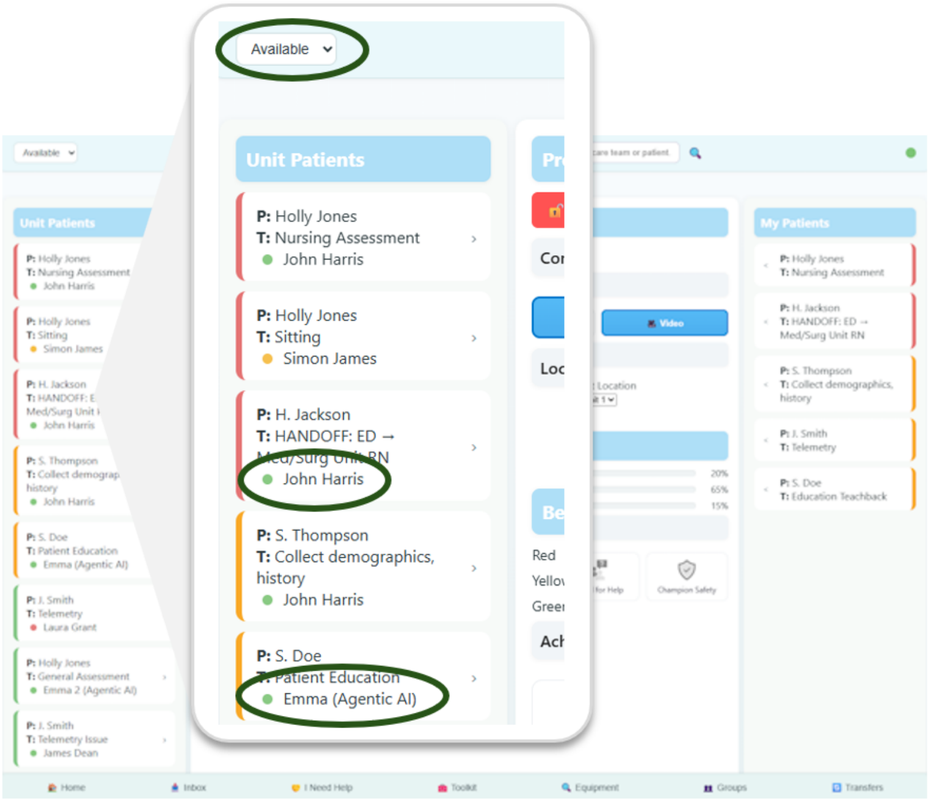
Implementation in Nursing First

In the Nursing First model, a patient-facing agent such as Emma will not conduct an assessment unless the system confirms that a physical nurse or staff member is available to respond if escalation is required. A phrase like "Stop, I need help" only has meaning if help can arrive.

This design anchors AI behavior in real-world capacity rather than in abstract availability, directly addressing the "false safety" problem documented in telehealth studies, in which patients received automated responses but lacked timely clinical intervention [25,26,79].

Research on clinical alarm systems demonstrates that alerts disconnected from response capacity led to alarm fatigue and desensitization [80,81]. Capacity awareness prevents this failure mode by ensuring that AI operates only within the system's confirmed capabilities.

"If I'm not physically available to respond, the assessment doesn't start. That protects my patient—and it protects me."



Co-Intelligence 4.1: MyAction Hub was driven by research emphasizing the need to be aware of the care team's status and availability. Agentic AI doubles down on this awareness to ensure agents are used safely, and the care team is ready to respond.

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4.1 Co-Intelligence Through Capacity Awareness

Vignette: Knowing Help Is Actually Available

When a patient starts an assessment with Emma, I know it's safe because it won't begin unless someone like me is physically available to respond. If a patient says, "Stop, I need help," Emma stops immediately and escalates—and I'm already assigned and able to step in. That matters. Emma never gives patients a false sense of safety, and I don't have to worry that a virtual tool is operating beyond what our staffing can support.

Evidence-Based Measures

Potential Measure	Illustrative Instrument/Method	Illustrative Target Statement	Potential Evidence Base
Assessment Start Compliance	System log audit + capacity verification [82]	100% compliance	Critical safety requirement
Escalation Success Rate	Time from escalation to first responder contact [68]	≥95% within 5 min	ED response time standards
False Safety Incidents	Patient safety event reporting [52]	Zero incidents	Patient safety priority
Capacity Prediction Accuracy	Real-time location system (RTLS) validation [83]	≥90% accuracy	Healthcare RTLS benchmarks
Patient Trust Calibration	Trust in Automation scale [84]	3.5-4.5/5.0 (calibrated)	Appropriate trust range

Research Support

Capabilities like MyAction Hub's capacity awareness capability is driven by research emphasizing the need to monitor the care team's status and availability [85,86]. Studies of interruption-driven work environments show that responder availability significantly impacts task completion and safety [20,32,34]. Agentic AI doubles down on this awareness to ensure agents are used safely, and the care team is ready to respond.

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4.2 Co-Intelligence Through Shared Responsibility Surfaces

Principle: Insight or action without ownership does not improve outcomes.

Theoretical Foundation

This principle draws from:

- **Common ground theory** [41,42]: Effective collaboration requires a shared understanding of who knows what and who is responsible for what
- **Distributed cognition** [35,36]: External representations (artifacts, displays) support collective cognitive work
- **Team coordination research** [63,64]: Explicit role clarity reduces coordination failures
- **Accountability frameworks** [58,59]: Clear ownership improves follow-through and reduces gaps

Implementation in Nursing First

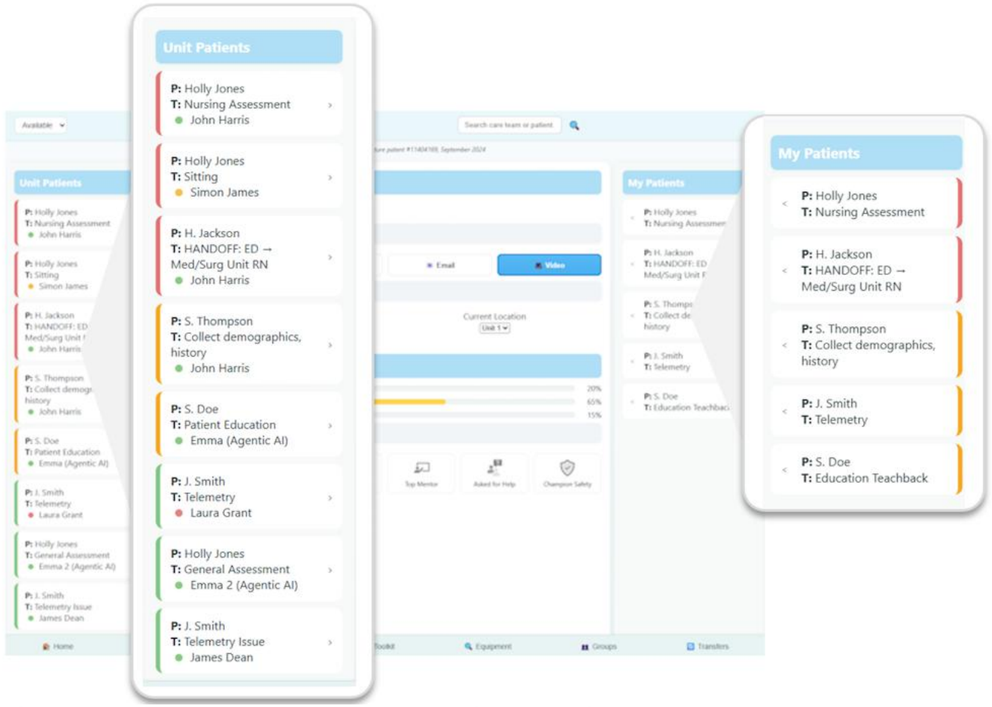
Capabilities like the Nursing First MyActionHub provide a shared operational surface where:

- Care plan responsibilities are visible to all team members
- Ownership is explicitly assigned and displayed
- Status is continuously updated in real-time
- AI-generated insights are routed directly to accountable clinicians

Rather than delivering information in isolation (which increases cognitive load without improving outcomes [22,31]), agents contribute to a system where responsibility is clear and coordinated across the care team.

Research on clinical information systems shows that lack of role clarity and information overload are primary causes of adverse events [87,88]. Shared responsibility surfaces address both issues by making ownership explicit and reducing unnecessary information exposure.

"I don't have to wonder who's handling what. If it's flagged, it's owned—and everyone can see it."



Co-Intelligence 4.2: MyAction Hub shows the full range of activities underway in the care setting. This information sits in the hands of each member of the care team. On the left it shows all the activities underway by the care team. On the right are the specific responsibilities of a care team member.

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4.2 Co-Intelligence Through Shared Responsibility Surfaces

Vignette: No More “Who’s Handling This?”

After Emma completes an assessment, I don’t have to dig through a report or wonder if anyone else saw the same flags I did. The results show up directly in MyAction Hub, with clear ownership. One follow-up is assigned to me, another to a virtual nurse.

That visibility matters. I can see what’s been addressed, what’s pending, and who is responsible. Nothing disappears into a note or an inbox. If something isn’t done, it’s obvious—and if it is done, I don’t duplicate work.

Evidence-Based Measures

Potential Measure	Illustrative Instrument/Method	Illustrative Target Statement	Potential Evidence Base
Ownership Clarity Index	Survey: "I always know who is responsible" [71]	≥4.5/5.0	Team collaboration assessment
Duplicate Work Rate	Process mining: duplicate interventions [69]	<5% of tasks	Workflow efficiency benchmark
Information Findability	Time to locate task status [89]	<30 seconds	Usability standard
Task Completion Rate	% of assigned tasks completed on time [90]	≥90%	Clinical workflow benchmarks
Coordination Errors	TeamSTEPPS assessment [91]	<2 per 1,000 patient days	Team performance standard
Common Ground Accuracy	Team Mental Model concordance [72]	≥80% agreement	Shared understanding measure

Research Support

Capabilities like MyAction Hub's shared responsibility surface operationalize research showing that team performance depends on common ground—shared knowledge of who knows what, who is doing what, and what has been accomplished [41,42,72]. Studies demonstrate that explicit visualization of responsibility improves task completion rates and reduces coordination errors in healthcare teams [63,64,92].

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4.3 Co-Intelligence Through Human-Initiated Delegation

Principle: Agents are invoked intentionally, not unleashed automatically.

Theoretical Foundation

These principal addresses:

- **Automation bias** [23,37]: Users over-rely on automated suggestions when they appear automatically
- **Professional autonomy** [93,94]: Nurses require control over clinical decisions to maintain accountability
- **Human-automation interaction** [75,95]: Human-initiated automation preserves situational awareness better than fully automated systems
- **Cognitive forcing functions** [96]: Requiring explicit action prevents automatic acceptance of recommendations

Implementation in Nursing First

Through capabilities like MyActionHub, nurses choose when to engage:

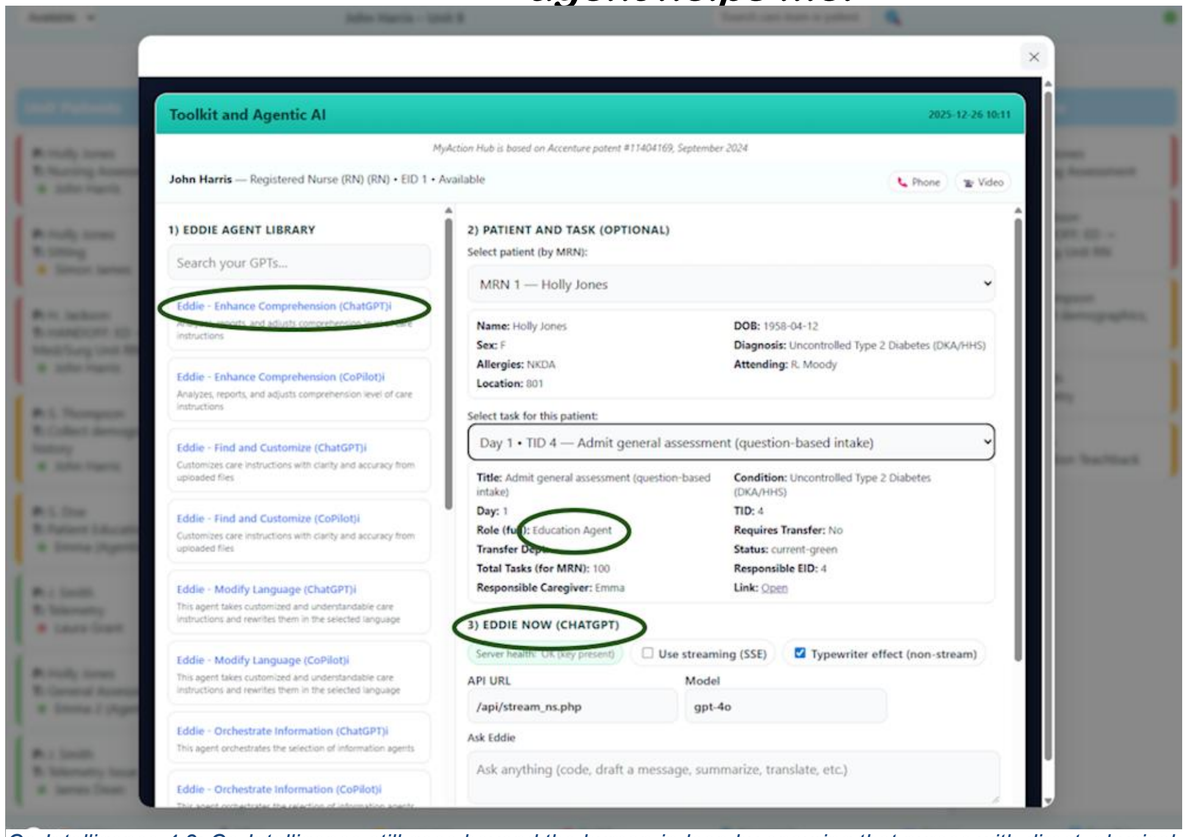
- **Emma** for patient assessment and education
- **Eddie** for task support and personalization
- **Otto** for communication and coordination
- **Seer** for pattern recognition and next-step guidance

No agent auto-chains into another unless by design. Sequencing remains a human potential decision, preserving professional judgment and reducing automation bias [23,37].

Research on clinical decision support shows that automatically presented alerts and recommendations are more likely to be ignored or accepted uncritically [97,98]. Human-initiated systems require active engagement, which enhances situational awareness and reduces inappropriate reliance on automation [75,95].

Co-intelligence does not mean AI decides what happens next. It means humans decide which intelligence to bring in.

"The system doesn't decide what happens next. I do—and I choose which agent helps me."



Co-Intelligence 4.3: Co-Intelligence still goes beyond the human-in-loop by ensuring that nurses with direct, physical responsibility for a patient's care can use and control how agentic AI capabilities enable care delivery. Care team members in a care setting have access to agentic AI and GenAI capabilities in their toolbox and ensure that a patient is the center of how these tools are used.

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4.3 Co-Intelligence Through Human-Initiated Delegation

Vignette: Decide Which Agent to Use—and When

When I see that a patient is confused about their medications, the system doesn't make assumptions or act on its own. I decide what happens next—whether that's using Eddie for tailored education, Otto to notify the RN, or Seer to anticipate follow-up needs. The agents support me, but they don't override my judgment or sequence care for me, which keeps me in control and reduces automation bias.

Evidence-Based Measures

Potential Measure	Illustrative Instrument/Method	Illustrative Target Statement	Potential Evidence Base
Agent Invocation Pattern	System log analysis: human vs. auto-initiated [99]	≥90% human-initiated	User control measure
Automation Bias Rate	Clinical decision concordance analysis [37,100]	<10% inappropriate concordance	Automation bias benchmark
Professional Autonomy	Nursing Work Index [101]	≥2.5/4.0	Professional practice environment
Situational Awareness	SAGAT (Situation Awareness Global Assessment) [102]	≥70% accuracy	SA measurement standard
Decision Quality	Clinical outcome + process appropriateness [103]	≥85% appropriate	Decision quality benchmark
User Control Satisfaction	System Usability Scale [104]	≥68/100	Usability benchmark

Research Support

Human-initiated delegation operationalizes findings from automation bias research showing that users who actively choose to engage with automated tools maintain better situational awareness and make higher-quality decisions than passive recipients of automated recommendations [23,37,75,95]. This design preserves the professional judgment that distinguishes nursing practice from task execution [93,94].

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4.4 Co-Intelligence Through Structured Team Interaction

Principle: Interruption, oversight, and recovery are routine operations, not failure states.

Theoretical Foundation

This principle is grounded in:

- **Interruption science** [20,32,34,105]: Nursing work is inherently interrupt-driven; systems must support rather than resist this reality
- **Resilience engineering** [27,28,76]: Successful systems degrade gracefully and support recovery
- **Team cognition research** [72,106]: Effective teams maintain shared context during disruptions
- **Workflow continuity** [107,108]: Supporting task resumption reduces errors and cognitive load

Implementation in Nursing First

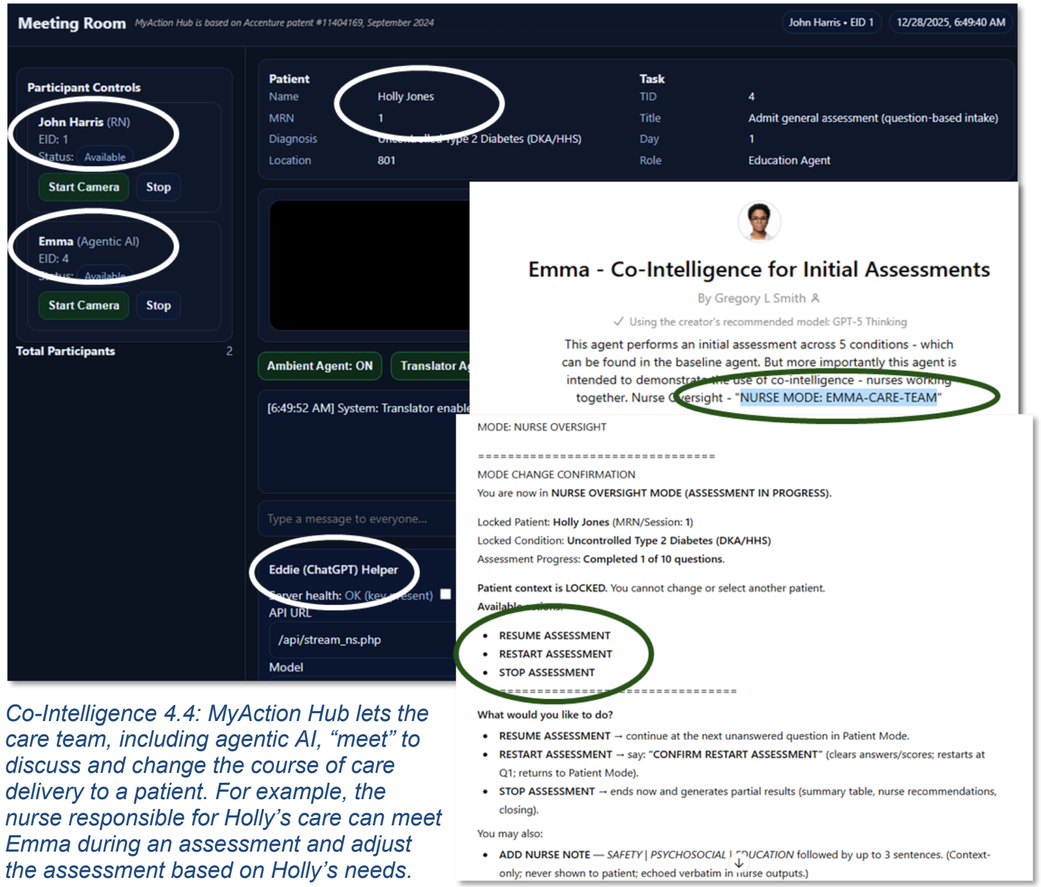
Real nursing work is interrupt-driven. Studies document that nurses experience numerous interruptions per hour during medication administration alone, with task durations averaging just 2-3 minutes [49,50]. Traditional AI systems treat interruptions as failures; co-intelligent systems treat them as design.

In the Nursing First model:

- Assessments can be paused and resumed without data loss
- Context is preserved across interruptions
- Multiple team members can join ongoing work
- The system explicitly supports "handoff" states
- Recovery paths are built into workflows

Research shows that interruptions without recovery support led to resumption errors, in which clinicians forget previous steps or duplicate work [32,105,109]. Systems designed for interruption reduce these errors significantly [107,108].

"Stopping an assessment isn't failure. It's reality—and the system doesn't punish me for it."



Co-Intelligence 4.4: MyAction Hub lets the care team, including agentic AI, "meet" to discuss and change the course of care delivery to a patient. For example, the nurse responsible for Holly's care can meet Emma during an assessment and adjust the assessment based on Holly's needs.

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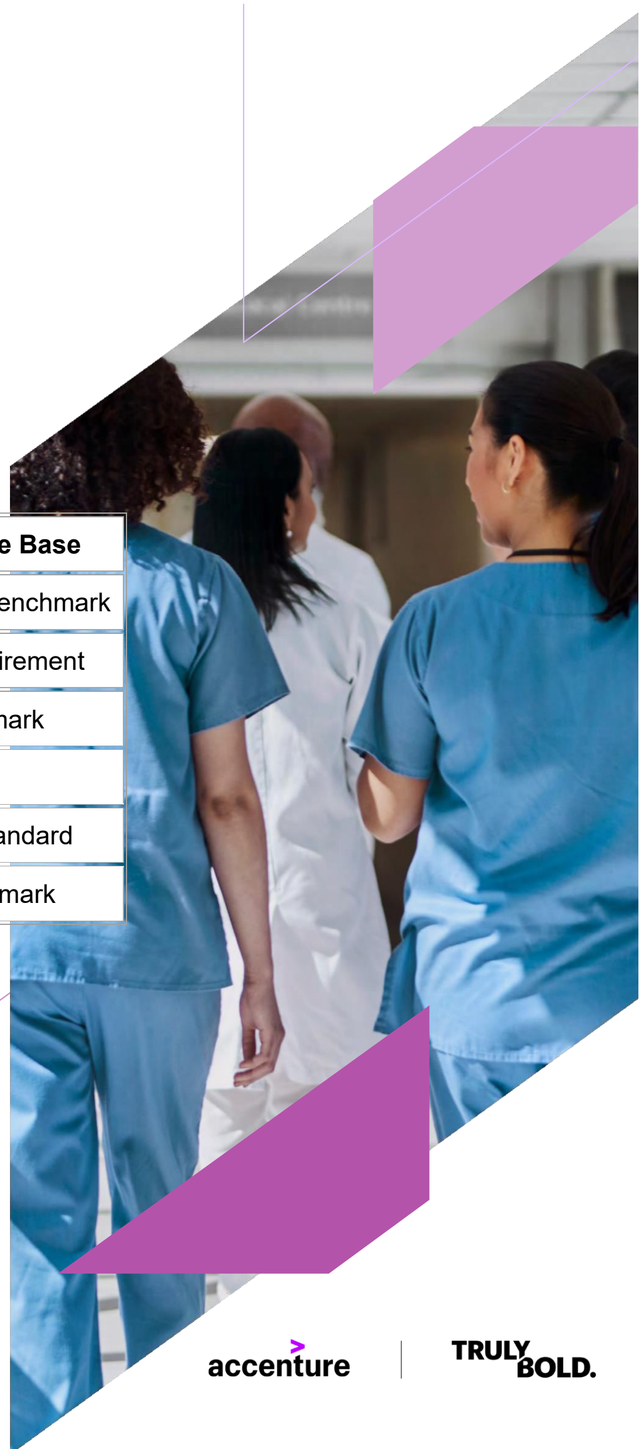
4.4 Co-Intelligence Through Structured Team Interaction

Vignette: Interrupting Without Losing Context

When I see that a patient is confused about their medications, the system doesn't make assumptions or act on its own. I decide what happens next—whether that's using Eddie for tailored education, Otto to notify the RN, or Seer to anticipate follow-up needs. The agents support me, but they don't override my judgment or sequence care for me, which keeps me in control and reduces automation bias.



Evidence-Based Measures

Potential Measure	Illustrative Instrument/Method	Illustrative Target Statement	Potential Evidence Base
Interruption Recovery Rate	% of interrupted tasks resumed successfully [107]	≥95%	Workflow continuity benchmark
Context Preservation Accuracy	User verification after resumption [108]	≥90% accurate	Memory support requirement
Resumption Error Rate	Errors during task resumption [109]	<5% of resumptions	Patient safety benchmark
Recovery Time	Time from interruption to successful resumption [110]	<2 minutes	Workflow efficiency
Team Handoff Quality	I-PASS handoff assessment [70]	≥4.0/5.0	Structured handoff standard
Cognitive Load During Interruption	NASA-TLX subscale [53]	<60/100	Human factors benchmark

Research Support

Capabilities like MyAction Hub's interruption-resilient design are informed by extensive research on interruption management in healthcare [20, 32, 34, 105]. Studies show that supporting graceful interruption and recovery reduces errors, maintains situational awareness, and lowers cognitive burden [107,108,109]. The system enables care team members, including AI agents, to "meet" to discuss and dynamically adjust care delivery capability that mirrors effective team huddles documented in TeamSTEPPS research [91,111].

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4.5 Co-Intelligence Through an Agent Ecology

Principle: Intelligence emerges from coordinated specialists, not monolithic capability.

Theoretical Foundation

This principle synthesizes:

- **Distributed cognition** [35,36,40]: Intelligence resides in the system of interactions, not individual agents
- **Team diversity research** [112,113]: Specialized expertise outperforms generalist capability in complex domains
- **Resilience engineering** [27,28,76]: Distributed systems degrade gracefully; centralized systems fail catastrophically
- **Multi-agent systems** [114,115]: Coordination protocols enable emergent intelligence
- **Cognitive load theory** [116,117]: Distributed processing reduces individual cognitive burden

Implementation in Nursing First

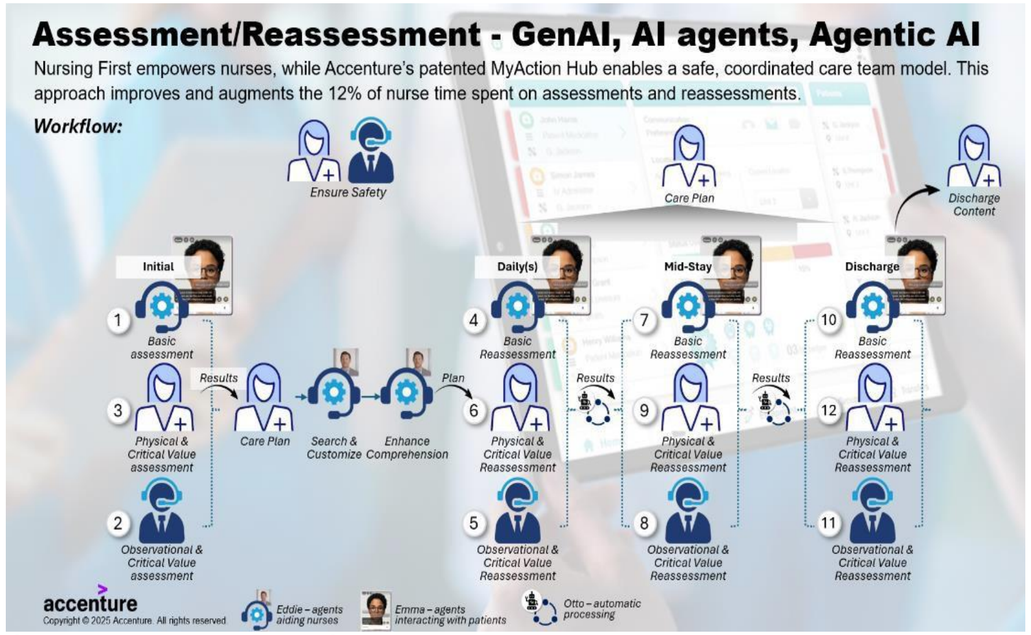
There is no single "AI" in a Nursing First system. Instead, intelligence emerges from an ecology of roles:

- **Registered Nurses**: Clinical judgment, physical assessment, patient advocacy
- **Virtual Nurses**: Remote oversight, documentation support, care coordination
- **Emma** (assessment): Structured data collection, standardized protocols
- **Eddie** (support): Patient education, personalized guidance
- **Otto** (coordination): Communication routing, team awareness
- **Seer** (anticipation): Pattern recognition, proactive recommendations

Each agent performs a distinct, bounded cognitive function. No single agent carries end-to-end responsibility or attempts to replace human judgment. Together, this ecology forms a distributed cognitive system that is more resilient and trustworthy than any standalone agent.

Research on team cognition shows that diverse, specialized teams outperform generalists in complex problem-solving [112,113]. Studies of multi-agent systems demonstrate that properly coordinated agents achieve emergent intelligence superior to monolithic systems [114,115]. In healthcare specifically, research documents that distributed decision-making with clear role boundaries reduces errors and improves outcomes [63,64,118].

"No single agent carries the risk. The team does—and I stay accountable without being overloaded."



Co-Intelligence 4.5: The key to Co-Intelligence is like the key to agentic AI: ensuring the care team operates within a process and workflow designed around nurses in the care setting, virtual nurses, and various classes of agentic AI. Together, they provide patient-centric care and support one

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4.5 Co-Intelligence Through an Agent Ecology

Vignette: No One Agent Carries the Risk Alone

In my day-to-day work, care comes from a team, not from a single system. Each agent supports a different part of the work, while I stay accountable for what happens next. If one agent isn't available or something doesn't fit, the system degrades gracefully—and patient care keeps moving.

Evidence-Based Measures

Potential Measure	Illustrative Instrument/Method	Illustrative Target Statement	Potential Evidence Base
Role Distribution Balance	Task allocation analysis across agents [119]	No single agent >40% tasks	Load distribution principle
Cognitive Load Distribution	NASA-TLX by role/agent [53]	All roles <60/100	Distributed cognition goal
System Degradation Impact	Patient outcomes during agent unavailability [120]	<10% performance decrease	Resilience requirement
Emergent Team Performance	Team effectiveness score [121]	≥4.0/5.0	Team outcome measure
Handoff Quality Between Agents	Agent-to-agent coordination errors [122]	<5% of transitions	Multi-agent coordination
Role Clarity	Team Role Survey [123]	≥4.5/5.0	Role definition measure

Research Support

The agentic ecology model operationalizes distributed cognition theory [35,36,40], which demonstrates that intelligence in complex systems emerges from coordination among specialized components rather than centralized processing. Healthcare research shows that well-coordinated teams with clear role differentiation achieve better outcomes than individuals or poorly structured groups [63,64,118,124]. Multi-agent systems research provides design principles for coordination protocols that enable reliable emergent behavior [114,115,125].

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5. What This Changes About How We Design AI in Healthcare

Designing for co-intelligence fundamentally changes design priorities and evaluation criteria:

Design Principal Shifts

Traditional AI Priority	Co-Intelligence Priority	Research Support
Autonomy	Coordination	[35,36,40,63,64]
Forced completion	Recoverability	[27,28,107,108]
Clever prompts	Role clarity	[41,42,72,123]
AI confidence scores	Human-governed escalation	[18,19,68,126]
Artificial completeness	Partial results with explicit boundaries	[60,61,127]
Individual capability	Distributed intelligence	[35,36,112,113]
Automation	Augmentation	[75,93,94,128]

Evaluation Framework Changes

Traditional AI evaluation focuses on:

- Accuracy on test sets
- Speed of processing
- Autonomous task completion

Co-intelligence evaluation focuses on:

- Team coordination quality [71,91,121]
- Recovery from interruption [107,108,109]
- Appropriate trust calibration [84,134]
- Cognitive load distribution [53,116]
- Role clarity and shared understanding [72,123]
- Safety event rates [52,68]
- Human authority preservation [93,94,101]

These shifts align with emerging evidence that AI's most significant value in healthcare lies in augmenting workforce capacity and coordination—not replacing clinical judgment [4,5,129,130]. Recent systematic reviews of AI in healthcare consistently show that hybrid human-AI systems outperform either alone when coordination mechanisms are properly designed [131,132,133].

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5. What This Changes About How We Design AI in Healthcare

Governance and Managing Change

Governance and change management are foundational to designing AI systems that truly augment nursing practice. Research on healthcare technology adoption demonstrates that governance mechanisms significantly impact both safety outcomes and user acceptance [43,44,66,67,135].

By establishing clear policies for coordination, recoverability, and escalation, organizations safeguard against unintended consequences and maintain human authority. Change management efforts—such as pilot programs, education, and transparent evaluation—enable teams to embrace new technologies confidently, ensuring that AI adoption enhances rather than disrupts care delivery [46,47,136,137].

Evidence-Based Measures

Potential Measure	Illustrative Instrument/Method	Illustrative Target Statement	Potential Evidence Base
Coordination Quality	CSACD instrument [71]	≥4.0/5.0	Team collaboration standard
Recoverability Success	% of disruptions recovered without error [107]	≥95%	Workflow continuity goal
Role Clarity	Team Role Awareness Survey [123]	≥4.5/5.0	Team coordination measure
Escalation Path Compliance	Audit of escalations following protocol [126]	≥98%	Safety-critical requirement
Appropriate Trust	Trust in Automation scale [84,134]	3.5-4.5/5.0	Calibrated trust range
Human Authority Preservation	Nursing Work Index autonomy subscale [101]	≥2.5/4.0	Professional practice measure
System Usability	System Usability Scale [104]	≥70/100	Industry usability standard

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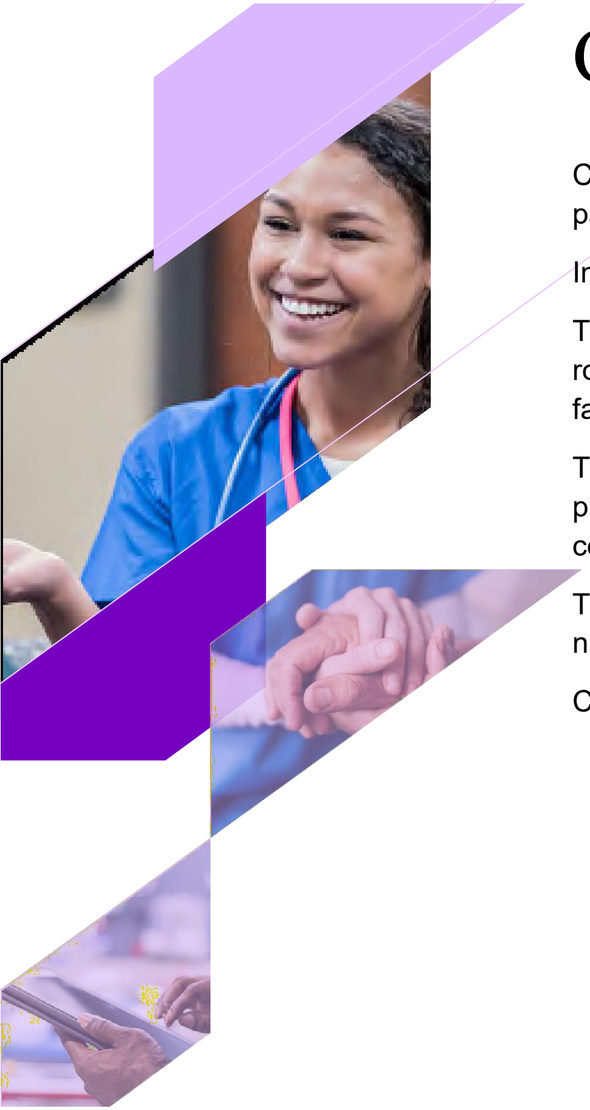

Closing: Co-Intelligence is a Design Choice

Co-intelligence is not something added after deployment. It is a design choice made at the beginning—when defining roles, escalation paths, and how humans and AI share context.

In nursing care, this choice is the difference between tools that assist and systems that can be trusted.

The research evidence is clear: effective human-AI collaboration in safety-critical domains requires explicit coordination mechanisms, role clarity, and human governance [35,36,40,75,131,132]. Healthcare AI systems that prioritize autonomy over coordination consistently fail to deliver sustainable value [9,10,77,138].

The Nursing First co-intelligence framework offers a path forward grounded in distributed cognition theory, high-reliability organization principles, and empirical evidence from nursing workflow research. While the specific integration requires prospective validation, each component draws from established findings across multiple research domains.

The question is not whether AI will transform nursing care—it already is. The question is whether that transformation will empower nurses or overwhelm them, whether it will enhance coordination or fragment it, and whether it will build trust or erode it.

Co-intelligence is how we ensure the answer is the former.

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