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CHALLENGES IN CHANGE MANAGEMENT FOR AI-DRIVEN PREDICTION TOOLS IN PUBLIC HOSPITAL CLINICAL WARDS: THE CASE OF MROC IMPLEMENTATION

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ABSTRACT

The integration of artificial intelligence (AI) in healthcare offers significant opportunities to enhance clinical decision-making and patient outcomes. However, AI adoption in public hospital settings presents various challenges, particularly concerning clinician resistance, concerns over predictive accuracy, and the perceived threat to traditional clinical judgment. This study examines the implementation of the Modelling Risks and Outcome Calculations (mROC) tool, an AI-driven predictive system developed to reduce hospital-acquired complications (HACs) at North Metropolitan Health Service (NMHS).

The mROC pilot demonstrated notable success, particularly in reducing urinary tract infections (UTIs) within a neurosurgery ward, achieving a 48% reduction in UTI rates per 1,000 bed days and an estimated cost savings of $AUD406,758 over three months. Despite these promising results, significant barriers hindered broader implementation. Resistance stemmed from the disruption of established clinical workflows, scepticism regarding AI-driven predictions, and concerns about increased scrutiny over clinical decision-making.

Furthermore, disparities between mROC risk assessments and traditional clinical assessments generated uncertainty about the tool's reliability. Limited clinician engagement in the tool's development also contributed to reluctance in its adoption, emphasising the importance of co-design in AI integration.

This paper identifies key lessons from the mROC implementation, highlighting the necessity of early clinician involvement, transparent communication of AI effectiveness, and strategies for aligning AI tools with clinical workflows. Recommendations include structured change management approaches, iterative pilot trials, and improved real-time adaptability of AI models to evolving patient conditions. By addressing these challenges, AI-driven tools like mROC can foster sustainable adoption, optimising patient care while supporting clinical decision-making in public hospital settings.

KEYWORDS

artificial intelligence (AI), Change Management, Public Hospital

INTRODUCTION

The integration of artificial intelligence (AI) in healthcare has the ability to transform clinical decision-making by offering predictive tools that improve patient outcomes and operational efficiency. However, despite its potential, the implementation of AI-based solutions in public hospital settings faces considerable challenges, particularly due to human factors such as resistance to change, fear of job displacement, and concerns about accountability.

This paper explores the implementation of the mROC tool, an evidence-based AI-driven predictive system designed to improve patient safety by identifying individuals at high risk of hospital-acquired complications (HACs). The study evaluates the reluctance of healthcare professionals to adopt AI-driven assessments, examines concerns about its predictive accuracy, and compares mROC to traditional risk assessment models used for falls and infection prevention.

IDENTIFIED PROBLEMS

Hospital-acquired complications (HACs) such as falls, UTIs, pressure injuries, and aspiration pneumonia significantly impact patient outcomes and hospital resource allocation. These conditions are not only detrimental to patient health but also result in increased lengths of stay, higher morbidity, and financial strain on healthcare systems. At NMHS, data showed that patients with HACs had hospital stays six times longer than those without, with total costs amounting to $AUD49.4 million in the 2022/23 financial year and $AUD1.5 million in penalties for safety performance shortfalls.

In response to this critical issue, NMHS developed the mROC tool to provide real-time, patient-specific risk assessments using AI and data science methods. The system applies logistic regression models to clinical and demographic data to identify high-risk patients early in their care trajectory.

PROJECT OBJECTIVES AND APPROACH

The mROC initiative aimed to shift risk assessment from a generalized, population-level model to an individualized approach that prioritizes high-risk patients for proactive intervention. Key objectives included:

- Enhancing patient safety by supporting early, targeted clinical interventions.
- Reducing the incidence and severity of HACs through predictive analytics.
- Demonstrating cost-effectiveness and improving healthcare delivery efficiency.
- Engaging clinicians in a co-design process to align the tool with existing workflows.

A three-month pilot was conducted in a Neurosurgery ward, where the tool identified high-risk UTI patients using predictive markers. Interventions included educational posters, patient leaflets, and bedside visual cues. The results were compelling:

- 48% decrease in UTIs per 1,000 bed days.
- 55% absolute reduction in total UTI HACs.
- $AUD406,758 in direct cost savings.
- Projected $AUD10.5 million in annual savings if scaled system-wide.

Encouraged by these findings, NMHS expanded the mROC initiative to additional wards and clinical contexts.

CHALLENGES IN IMPLEMENTATION

Despite early success, scaling mROC across the organization revealed several critical challenges that limited its broader adoption [1]. These were categorised into four core areas:

CLINICAL ADOPTION AND WORKFLOW DISRUPTION

The transition to AI-supported care required significant behavioral and procedural adjustments. Clinicians had to incorporate mROC insights without additional staffing or system-level workflow restructuring. This integration gap caused friction, especially when mROC predictions conflicted with existing evidence-based tools such as traditional falls risk assessments.

The result was skepticism about whether the tool truly added value, especially when it labeled most patients as low-risk, in contrast to conventional protocols that assumed higher default risk levels. This disconnect created doubts about reliability and fueled resistance among staff.

RESISTANCE ROOTED IN HUMAN FACTORS

Healthcare professionals expressed strong concerns over the implications of AI integration. A major theme was fear that AI would reduce professional autonomy and shift accountability from collective clinical judgment to individual performance metrics. Nurses, in particular, feared mROC could be used to evaluate their effectiveness unfairly if predictive outcomes didn't align with clinical actions or patient results [2].

This mistrust was exacerbated by a lack of familiarity with AI technologies, underscoring a digital capability gap within the workforce. Many staff felt unprepared to interpret or contextualize the tool's recommendations, contributing to disengagement.

TECHNICAL LIMITATIONS IN PREDICTION

While the model's logic was statistically sound, it occasionally failed to capture real-time shifts in patient risk. The absence of a comprehensive electronic medical record (EMR) system limited the model's responsiveness. For instance, a patient classified as low-risk upon admission might experience a deterioration in condition that the tool would not detect due to reliance on static, administrative data inputs.

Clinicians also noted that mROC occasionally underestimated risk levels for medium-high acuity patients while overestimating for those with lower risk, further undermining trust in its outputs.

LACK OF STAKEHOLDER ENGAGEMENT AND COMMUNICATION

Another major barrier was the perception that mROC was imposed on clinical teams without sufficient engagement. Many clinicians were unaware of its success in early trials due to limited communication about its impact, and felt excluded from decision-making processes. This led to skepticism, lack of ownership, and resistance to integration.

Moreover, stakeholders were unclear about how mROC would fit into the broader model of care, and who would be accountable for outcomes related to AI-generated predictions. Without a clear service delivery model, clinicians viewed the tool more as an administrative task than a clinical support system.

RESULTS AND FINDINGS

IMPACT OF RESISTANCE ON IMPLEMENTATION

Despite demonstrating success in preventing urinary tract infections during the initial three-month trial, the project encountered resistance from clinicians, leading to a narrowing of its original scope. As a result, plans to expand the rollout to include predictive models for falls and pressure injuries were postponed. Negative perceptions among clinical staff limited the system's uptake, necessitating a revision of engagement strategies to rebuild trust and promote collaboration. At an organisational level, NMHS is actively working to enhance digital maturity by strengthening the capabilities of its workforce, systems, and infrastructure. The resistance encountered in this initiative underscores a broader need for education and exposure to technology-enabled, data-informed models of care, especially within clinical environments where change is often met with caution.

One key lesson from the project is that the ambition of digital transformation must be balanced with the organisation's readiness for change. Aligning the pace of implementation with stakeholders' willingness to adapt is critical to achieving sustainable, long-term impact.

EFFECTIVENESS OF MROC TRIAL

The mROC pilot trial delivered strong evidence of clinical and financial benefits, particularly in reducing hospital-acquired urinary tract infections (UTIs). Over a six-month period, a Difference-in-Differences (DiD) analysis demonstrated a 41.6% reduction in UTI incidence, from 2.79 to 1.63 per 1,000 bed days, across trial wards, accompanied by a 69% reduction in associated hospital-acquired complication (HAC) penalties.

TABLE 1: COMPARISON ANALYSIS ON REPORTED UTI IN TRIAL WARDS - MARCH TO AUGUST

	2024				2025			
Trial Ward	**UTIs**	**Total Beddays**	**UTI rate per 1000 beddays**	**HACs Penalty**	**UTIs**	**Total Beddays**	**UTI rate per 1000 beddays**	**HACs Penalty**
Ward 5	10	4,979	2.01	$ 9,985	7	4,066	1.72	$ 2,891
Ward C17	14	4,964	2.82	$ 14,139	6	4,486	1.34	$ 7,489
Ward G51	6	5,578	1.08	$ 6,371	7	5,179	1.35	$ 14,375
Ward G52	25	3,934	6.35	$ 132,925	9	3,966	2.27	$ 25,419
Ward G66	9	3,511	2.56	$ 25,276	5	3,123	1.60	$ 8,788
Total	**64**	**22,966**	**2.79**	**$ 188,697**	**34**	**20,820**	**1.63**	**$ 58,961**

These improvements translated into substantial cost savings, with the most significant reduction observed in Ward G52, where UTI rates declined from 6.35 to 2.27 per 1,000 bed days. Notably, this impact extended beyond numerical outcomes. The results reflected enhanced patient safety and strengthened the case for broader implementation of AI-assisted risk prediction tools.

However, questions were raised regarding whether these improvements stemmed solely from the mROC intervention or from general hospital-wide quality improvements. To address this, a comparative analysis between trial and non-trial wards was conducted. Trial wards showed a 31% greater improvement in UTI reduction than non-trial wards, where UTI rates decreased by only 10.6%. This differential reinforces the conclusion that the observed benefits were primarily attributable to the mROC intervention and not external systemic changes.

TABLE 2: COMPARISON ANALYSIS ON REPORTED UTI IN TRIAL AND NON-TRIAL WARDS- MARCH TO AUGUST

	2024			2025			Improvement
Wards Type	**UTIs**	**Total Beddays**	**UTI rate per '000 beddays**	**UTIs**	**Total Beddays**	**UTI rate per '000 beddays**	
Trial Wards	64	22,964	2.79	34	20,820	1.63	**41.6%**
Non-Trial Wards*	116	68,227	1.7	99	65,200	1.52	**10.6%**
Total	**180**	**91,191**	**1.97**	**133**	**86,020**	**1.55**	

The effectiveness of the mROC tool aligns with existing evidence on the power of data feedback and awareness in driving clinical improvement. For instance:

- The SENIC Project [6] demonstrated that simply providing feedback on surgical infection rates led to measurable improvements.
- A hospital-wide hand hygiene campaign in Geneva [7] reduced infection rates through awareness alone.
- Cochrane reviews and CAUTI (catheter-associated UTI) quality improvement initiatives [8] consistently support the use of feedback, unit-level awareness tools, and scorecards to influence behaviour.
- The Hawthorne Effect [9]—where individuals modify behaviour due to the awareness of being observed—further contextualises how increased attention via mROC may have impacted care practices.

In light of these outcomes, the study reinforces a critical insight: while AI tools like mROC are technologically robust, their true value is unlocked through strategic implementation that prioritises behaviour change, clinician engagement, and transparent performance monitoring.

Importantly, mROC functioned not only as a predictive engine but as a catalyst for heightened awareness and intervention.

Ultimately, the success of the mROC trial illustrates that the core challenge in AI deployment lies not in the algorithm itself, but in the human systems surrounding its adoption. The trial validates mROC's predictive efficacy and underscores the need for integrated change management approaches to support future scalability and sustainability.

CONCLUSION AND RECOMMENDATIONS

The implementation of AI-driven prediction tools like mROC offers a promising avenue for improving patient safety and optimising healthcare resources. However, challenges related to clinician resistance, concerns about predictive accuracy, and fears of increased accountability must be addressed to ensure successful adoption [3].

KEY RECOMMENDATIONS:

1. Establish change management functions from the outset of the idea [5] to ensure the solution aligns with clinical expectations and drives acceptance.
2. Enhance clinician engagement from early development stages to foster trust and collaboration.
3. Define the role of the tool in the model of care early to set the expectation of mROC as a clinical decision support rather than a hands-off clinical decision-making initiative to counteract concerns of accountability and job displacement.
4. Improve transparency and communication by sharing clear, data-backed evidence of AI effectiveness.
5. Ensure real-time adaptability of AI predictions to capture changing patient conditions.
6. Conduct phased pilot trials with clear success indicators to validate AI tools before full-scale adoption.
7. Foster a culture of learning and innovation, emphasising that failure in improvement projects will not be penalised.

By addressing these challenges, AI-driven clinical decision support tools like mROC can unlock new efficiencies in patient care while ensuring broad acceptance and sustainable integration into hospital workflows [4].

ETHICAL CONSIDERATIONS

This project was classified as a quality improvement initiative and, therefore, did not require formal ethics approval. Approval from the designated data custodian was obtained prior to accessing and analysing the data. The analysis utilised aggregated information sourced from the organisation's internal data repository, solely for the purpose of evaluating the impact of the pilot project. No interventions or modifications were made to existing system data.

Additionally, the outcomes of the pilot are not intended to inform or implement changes to clinical or administrative processes within the healthcare setting.

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