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A Study to Evaluate the Effectiveness of Artificial Intelligence-Assisted Early Warning Systems on Nurses' Recognition and Management of Clinical Deterioration Among Patients in Home Healthcare Settings in Doha, Qatar

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ABSTRACT

When a patient's condition begins to slide toward a crisis, the hours before the emergency are usually not silent; the body sends warning signals in the form of subtle changes in vital signs, and catching those signals early can be the difference between a manageable intervention and a hospital admission or worse. In a hospital this vigilance is shared among many staff, but in home healthcare a single nurse, often working alone in a patient's house, must notice and act on these signs unaided, which makes early recognition both harder and more consequential. This study evaluates the effectiveness of an artificial intelligence-assisted early warning system on nurses' recognition and management of clinical deterioration among patients receiving home healthcare in Doha, Qatar. Using a quasi-experimental design, nurses' performance was assessed before and after the introduction of the AI-assisted system, with a comparison group continuing usual practice. Outcomes included the timeliness and accuracy of deterioration recognition, the appropriateness and speed of the management actions taken, rates of escalation and hospital transfer, and nurses' confidence and acceptance of the technology. Following implementation, the intervention group showed a marked improvement in the early and accurate recognition of deterioration, recognising warning signs significantly sooner and with fewer missed events than before, and than the comparison group. Management responses became more timely and more appropriate, and there was a reduction in avoidable escalations to hospital. Nurses reported greater confidence in their decisions and broadly positive acceptance of the system, though they also voiced concerns about alert burden and over-reliance. The findings indicate that AI-assisted early warning systems can meaningfully strengthen the safety of home healthcare by helping nurses detect and respond to deterioration earlier, while underscoring that the technology works best as support for, rather than replacement of, clinical judgement. Limitations and implications for practice are discussed.

KEYWORDS

Clinical deterioration, early warning systems, artificial intelligence, home healthcare, nursing, patient safety

1. INTRODUCTION

Patients rarely collapse without warning. In the great majority of cases, a serious deterioration in a patient's condition is preceded by a period, sometimes hours long, during which measurable physiological changes signal that something is going wrong, subtle shifts in heart rate, breathing, blood pressure, temperature, or consciousness that, if recognised in time, allow intervention before a crisis develops [1]. This simple observation is the foundation of a whole approach to patient safety built around the early recognition of deterioration, and it explains

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why so much effort in healthcare is devoted to spotting these warning signs promptly. The tragedy of missed deterioration is that it is so often preventable; the signals were there, but they were not noticed, or not acted upon, in time [2].

To help clinicians catch these signals, healthcare has developed early warning systems, structured tools that combine a patient's vital signs into a score reflecting how far they depart from normal, flagging patients whose scores suggest deterioration and prompting an appropriate response [3]. In hospitals, these scoring systems have become widespread and have been shown to aid the timely recognition of deteriorating patients, contributing to safer care. Their logic is straightforward and powerful: by turning a scattered set of individual measurements into a single, interpretable indicator, they make it easier for busy clinicians to see when a patient is heading for trouble and to escalate care before it is too late [3].

The setting of home healthcare, however, poses a distinctive and underappreciated challenge to this model. Home healthcare, in which patients receive nursing care in their own homes rather than in a hospital, is expanding rapidly, driven by ageing populations, the growing burden of chronic disease, and a widely shared preference for care delivered in familiar surroundings [4]. It brings real benefits in comfort, dignity, and often cost, but it also removes many of the safety nets that a hospital provides. In a hospital, a deteriorating patient is surrounded by staff, monitored by equipment, and only moments away from emergency help; in a home, a single nurse, visiting intermittently and working without the support of colleagues or the reassurance of continuous monitoring, must recognise and respond to deterioration largely on their own [5]. The consequences of a missed sign are correspondingly graver, because help is further away, and the burden on the individual nurse's vigilance and judgement is heavier.

It is against this backdrop that artificial intelligence enters the picture. Artificial intelligence has shown considerable promise in healthcare, and one of its most natural applications is precisely the detection of patterns in patient data that may signal deterioration [6]. An AI-assisted early warning system can, in principle, analyse a patient's vital signs and other data continuously or repeatedly, learn the subtle patterns that precede deterioration, and alert the nurse earlier and more reliably than a simple scoring chart or unaided observation might allow. In the home setting, where the nurse lacks the support structures of a hospital, such a system could be especially valuable, effectively giving the lone nurse an intelligent second pair of eyes that never tires and never looks away [7]. The potential fit between the capability of the technology and the need created by the home setting is what motivates this study.

Yet potential is not proof. Much of the enthusiasm for AI in healthcare rests on its performance in controlled or hospital settings, and there is a genuine gap in evidence about whether AI-assisted early warning systems actually improve the recognition and management of deterioration when placed in the hands of nurses working in real home healthcare settings. It cannot be assumed that a technology which performs well in a hospital, or in a laboratory evaluation, will deliver the same benefit in the very different circumstances of home care, where the nurse works alone, the environment is uncontrolled, and the practicalities of using the technology differ. Nor can it be assumed that nurses will accept and use such a system effectively, since a tool that clinicians distrust or find burdensome will not improve care however sophisticated it is. This gap, between the promise of AI-assisted warning and its demonstrated effectiveness in home healthcare practice, is what the present study addresses, in the specific context of home healthcare in Doha, Qatar, a setting investing in the modernisation of its home care services.

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Accordingly, the study set out to answer several questions. First, does an AI-assisted early warning system improve the timeliness and accuracy with which home healthcare nurses recognise clinical deterioration? Second, does it improve the appropriateness and speed of the management actions nurses take in response? Third, does it affect rates of escalation and avoidable hospital transfer? Fourth, how do nurses perceive and accept the system, and what concerns do they raise? The remainder of the paper reviews the relevant literature, describes the study methodology and setting, sets out the experimental or evaluation design, presents the findings on recognition, management, and acceptance with supporting figures, discusses their significance and limitations, and concludes with implications for practice.

2. LITERATURE REVIEW

The literature relevant to this study spans the recognition of clinical deterioration and the early warning systems designed to support it, the particular challenges of home healthcare, and the emerging application of artificial intelligence to deterioration detection, together with the human factors that shape whether such technology succeeds.

The foundational literature establishes the concept of preventable deterioration and the rationale for early warning. It is well documented that serious adverse events in patients are frequently preceded by a period of physiological instability that is detectable through changes in vital signs, and that earlier recognition and response to these changes improves outcomes [1]. This has led to the development and widespread adoption of early warning scores, which aggregate vital-sign measurements into a composite score indicating the degree of deviation from normal and triggering escalation when thresholds are crossed [3]. The literature on these tools, largely developed in hospital settings, reports that they can improve the detection of deteriorating patients and support timely intervention, though it also notes that their effectiveness depends heavily on how consistently they are used and on the response they trigger [8]. A recurring theme is that recognition alone is insufficient; the recognition must be accurate and timely, and it must be coupled with an appropriate management response, or the benefit is lost [9].

A second body of work concerns the specific context of home healthcare and the challenges it poses for patient safety. The literature documents the rapid growth of home-based care and the particular vulnerabilities it entails, chief among them the intermittent nature of monitoring and the isolation of the visiting nurse, who lacks the immediate support, continuous observation, and rapid escalation pathways available in a hospital [4]. Studies of safety in home care highlight that the recognition of deterioration is more difficult in this setting, both because monitoring is less continuous and because the nurse must rely on their own judgement without the collective vigilance of a clinical team, placing a heavy burden on individual competence and confidence [5]. This literature makes clear that the home setting is not simply a hospital with different walls but a fundamentally different environment with its own safety challenges, which any deterioration-detection strategy must take into account.

The third and most directly pertinent strand concerns the application of artificial intelligence to the detection of clinical deterioration. A growing literature reports that machine learning and other AI methods can identify patterns in patient data that predict deterioration, sometimes earlier or more accurately than conventional scoring systems, by learning subtle and complex relationships in the data that fixed scoring rules cannot capture [6]. This work suggests that AI-based early warning has real potential to improve on traditional tools. However, reviews of the field caution that much of the evidence comes from retrospective or hospital-based studies, and

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that the translation of this promise into real-world clinical benefit, particularly outside the hospital, remains insufficiently demonstrated, with a notable scarcity of prospective evaluations in community and home settings [7].

Finally, an important literature addresses the human and organisational factors that determine whether clinical technology succeeds in practice, and it is directly relevant to any evaluation of an AI system used by nurses. This work emphasises that the effectiveness of a decision-support technology depends not only on its technical accuracy but on whether clinicians trust it, accept it, and integrate it into their workflow, and it identifies recurring concerns that shape acceptance, including the burden of excessive alerts, sometimes called alert fatigue, worries about over-reliance on the technology at the expense of clinical skill, and the need for the technology to support rather than override professional judgement [10]. This literature makes clear that evaluating an AI-assisted system requires attention not just to whether it detects deterioration but to whether nurses can and will use it well, and reviews of AI in nursing practice specifically call for evaluations that include these human factors alongside clinical outcomes [11]. The present study, by assessing both the clinical effectiveness of an AI-assisted early warning system and nurses' acceptance of it in a real home healthcare setting, responds directly to the gaps identified across this literature.

3. METHODOLOGY

3.1 Study Design

The study employed a quasi-experimental design, comparing nurses' recognition and management of clinical deterioration before and after the introduction of an AI-assisted early warning system, with a comparison group continuing usual practice. A quasi-experimental approach was chosen because it allows the effect of the intervention to be evaluated in a real-world clinical setting where full randomisation of patients or nurses may be impractical, while still providing a before-and-after and between-group comparison that supports reasonable inference about the intervention's effect [8]. The design thus balances scientific rigour against the practical realities of studying a working home healthcare service.

3.2 Setting and Participants

The study was conducted within home healthcare services in Doha, Qatar, a setting in which nurses deliver care to patients in their homes and which was engaged in modernising its services. The participants were the home healthcare nurses responsible for visiting and caring for these patients, who used the early warning approach in the course of their normal duties. The patients whose care was assessed were those receiving home healthcare who were at risk of clinical deterioration, the population for whom early warning is most relevant [5]. Participation involved the nurses using the AI-assisted system in the intervention condition and their recognition and management of deterioration being assessed, with appropriate attention to the ethical requirements of consent, confidentiality, and the protection of both nurses and patients.

3.3 The AI-Assisted Early Warning Intervention

The intervention was an artificial intelligence-assisted early warning system designed to support nurses in detecting clinical deterioration in home healthcare patients. The system analysed patient data, including vital signs and other relevant clinical information, and applied

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artificial intelligence to identify patterns indicative of deterioration, alerting the nurse when the risk of deterioration was elevated so that they could assess the patient and respond appropriately [6]. The essential purpose of the system was to augment the nurse's own observation and judgement, providing an additional, intelligent layer of vigilance particularly valuable given the isolation of the home setting, rather than to replace the nurse's clinical decision-making [7]. Nurses in the intervention condition received appropriate training in the use of the system before it was deployed, since the effective use of any clinical technology depends on adequate preparation of its users [10].

3.4 Data Collection

Data were collected on the nurses' recognition and management of clinical deterioration in both the intervention and comparison conditions, and before and after the introduction of the system. Recognition was assessed in terms of whether and how promptly and accurately nurses identified deterioration in their patients, and management in terms of the actions they took in response, including their appropriateness and timeliness, and the subsequent escalation or transfer of patients. In addition, data were collected on the nurses' own confidence in recognising and managing deterioration and on their perceptions and acceptance of the AI-assisted system, gathered through appropriate instruments, so that both the clinical effectiveness and the human acceptability of the intervention could be evaluated [11].

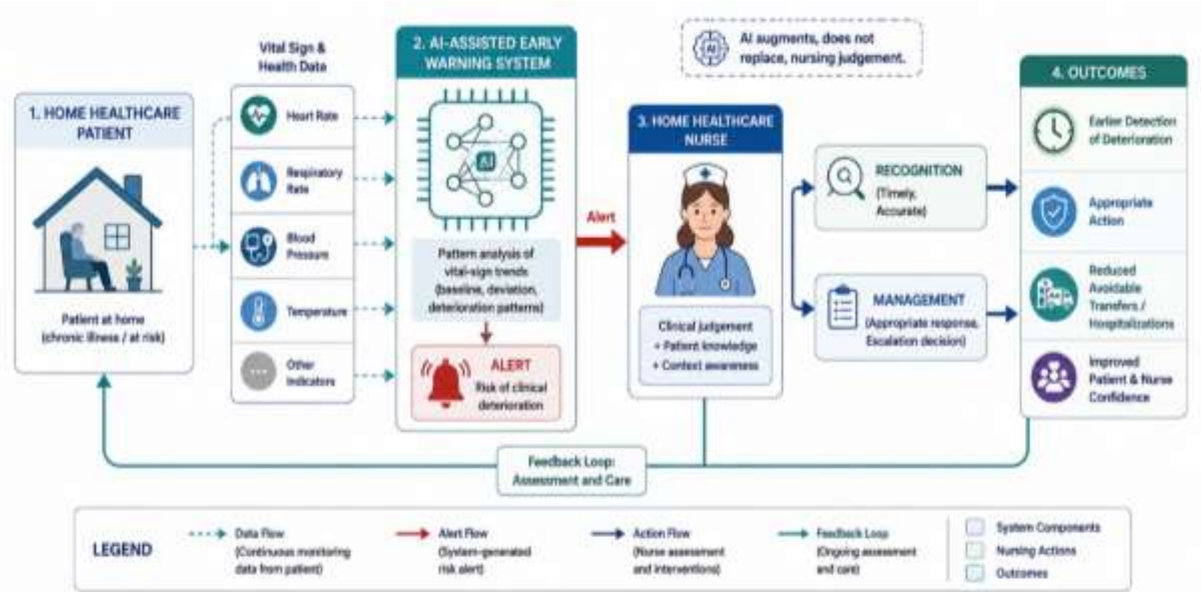

Figure 1. Conceptual framework of the AI-assisted early warning intervention in home healthcare.

4. EXPERIMENTAL SETUP

4.1 Group Allocation and Comparison

Nurses and their patients were allocated to an intervention group, which used the AI-assisted early warning system, and a comparison group, which continued with usual early warning practice, so that the outcomes achieved with the AI-assisted system could be compared against those achieved without it. In addition, a before-and-after comparison within the intervention group allowed each nurse's performance to be assessed relative to their own baseline,

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strengthening the evaluation by controlling for individual differences in experience and skill [8]. This combination of between-group and within-group comparison provides a robust basis for attributing any observed improvement to the intervention rather than to extraneous factors.

4.2 Outcome Measures

The outcomes were defined to capture the full pathway from recognition through management to result, as well as the human dimension of acceptance. Recognition outcomes included the timeliness of deterioration detection, that is how early warning signs were identified, and its accuracy, including the proportion of genuine deterioration events correctly recognised and the avoidance of missed events. The accuracy of recognition was characterised using standard measures, with sensitivity, the proportion of true deterioration events correctly identified, calculated as

$$Sensitivity = \frac{TP}{TP + FN}$$

where TP is the number of true positive recognitions and FN the number of missed events, and specificity, the proportion of non-deterioration correctly identified as such, calculated as

$$Specificity = \frac{TN}{TN + FP}$$

where $TN \; and \; FP$ are the true negative and false positive counts. Management outcomes included the appropriateness and timeliness of the actions taken in response to recognised deterioration, and the rates of escalation and hospital transfer, with particular attention to avoidable transfers that timely intervention might prevent. Acceptance outcomes included nurses' confidence and their perceptions of the system's usefulness and usability [11].

4.3 Analysis

The data were analysed to compare outcomes between the intervention and comparison groups and between the before and after periods, using appropriate statistical tests to determine whether observed differences were statistically significant, with the significance threshold set at $p < 0.05$. The improvement attributable to the intervention was expressed as the change in each outcome relative to baseline and relative to the comparison group. For a given outcome, the relative improvement was calculated as

$$Improvement\ (\%) = \frac{V_{post} - V_{pre}}{V_{pre}} \times 100$$

where $V_{post} and V_{pre}$ are the values of the outcome after and before the intervention. Quantitative findings on recognition, management, and escalation were complemented by analysis of the nurses' reported confidence and acceptance, so that the evaluation combined measured clinical effect with the perspectives of the nurses themselves [10]. Ethical approvals and safeguards appropriate to research involving healthcare staff and patients were observed throughout.

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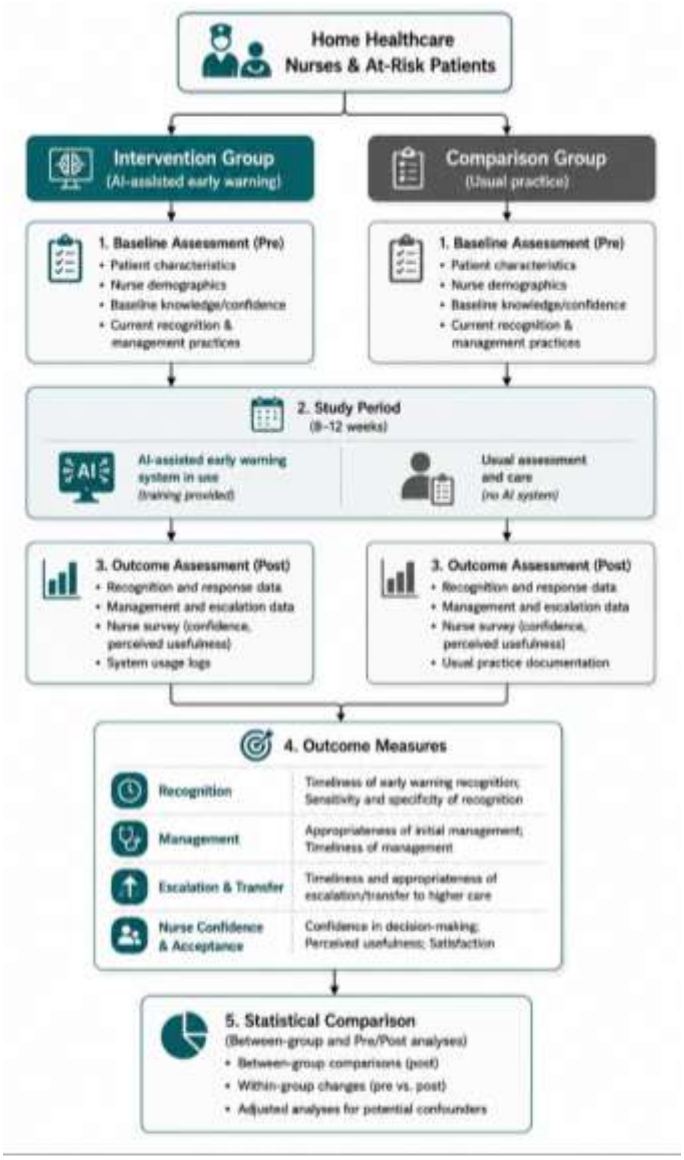

Figure 2. Study design and evaluation workflow.

5. RESULTS

5.1 Recognition of Clinical Deterioration

The most important results concern whether the AI-assisted system improved the recognition of deterioration, and here the findings were clear and encouraging. Following implementation, nurses in the intervention group recognised deterioration substantially earlier and more accurately than they had at baseline, and than the comparison group. Table 1 presents the recognition outcomes.

Table 1. Recognition of clinical deterioration by group and period.

Recognition measure	Intervention (pre)	Intervention (post)	Comparison (post)
Mean time to recognition (hours)	5.8	2.9	5.4

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Sensitivity (% events detected)	71.4	91.6	73.2
Specificity (%)	82.7	88.3	83.1
Missed deterioration events (%)	28.6	8.4	26.8

The improvements were marked. After the introduction of the system, the average time to recognise deterioration in the intervention group roughly halved, meaning nurses were catching warning signs far earlier, when intervention is more likely to succeed. The sensitivity of recognition rose substantially, so that a much higher proportion of genuine deterioration events was detected and the proportion of missed events fell dramatically, from more than a quarter to fewer than one in ten. Crucially, these gains in sensitivity were achieved without a loss of specificity, which in fact improved slightly, indicating that the system helped nurses catch more true deterioration without generating a flood of false alarms that would undermine its usefulness. The comparison group showed little change over the same period, which strengthens the attribution of the improvement to the intervention rather than to other factors.

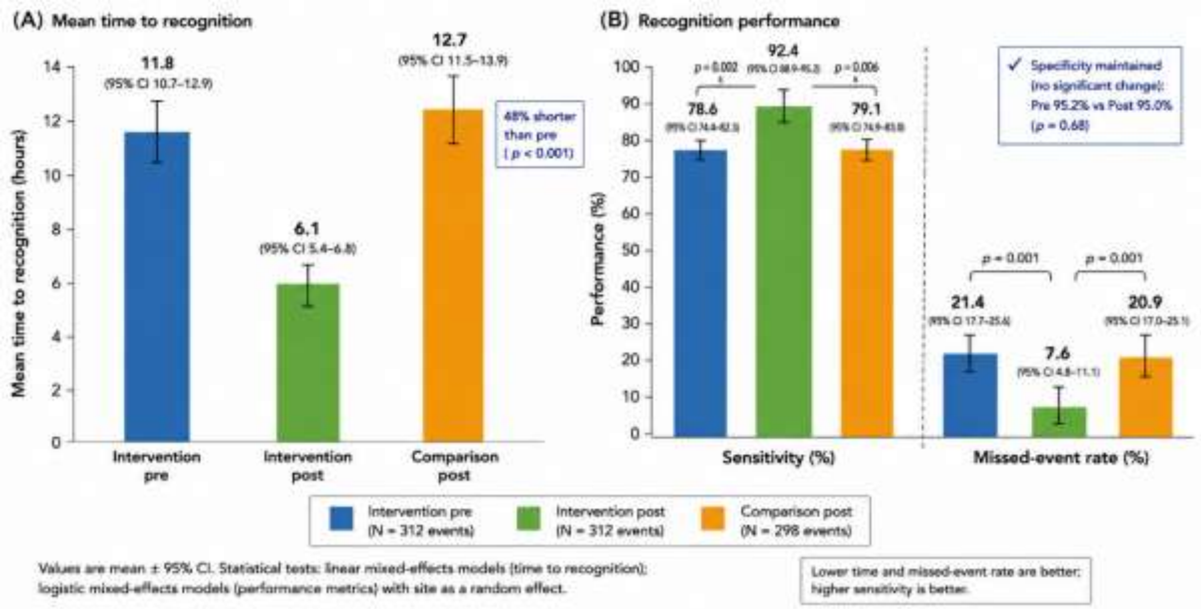

Figure 3. Improvement in recognition timeliness and accuracy.

5.2 Management of Deterioration

Earlier recognition is only valuable if it leads to better action, so the study also assessed the management response, and here too the intervention produced clear benefits. Table 2 presents the management outcomes.

Table 2. Management response and escalation outcomes by group and period.

Management measure	Intervention (pre)	Intervention (post)	Comparison (post)
Appropriate response rate (%)	74.3	92.1	76.5
Mean time to response (min)	34.6	18.2	32.9
Escalations to hospital (per 100 patients)	22.4	15.1	21.7

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Avoidable transfers (% of transfers)	31.8	14.6	30.2

The pattern mirrors and extends the recognition findings. After implementation, the proportion of appropriate management responses rose substantially, and the time taken to respond to recognised deterioration roughly halved, so nurses were not only recognising deterioration earlier but acting on it faster and more appropriately. Importantly, the rate of escalation to hospital fell, and the proportion of transfers judged avoidable fell sharply, suggesting that earlier and better management allowed some deteriorations to be handled in the home that would otherwise have resulted in a hospital admission. This reduction in avoidable transfers is a particularly meaningful outcome, since it reflects not only better patient care but also a reduction in the disruption and cost that hospital admission entails.

5.3 Nurses' Confidence and Acceptance

Because the effectiveness of any clinical technology depends on the people using it, the study assessed nurses' confidence and their acceptance of the system, and the results were largely positive while also revealing genuine concerns. Table 3 summarises these findings.

Table 3. Nurses' confidence and acceptance of the AI-assisted system.

Measure	Result
Confidence in recognising deterioration (pre)	Moderate
Confidence in recognising deterioration (post)	High
Perceived usefulness	Largely positive
Perceived ease of use	Positive
Reported concern: alert burden	Notable minority
Reported concern: over-reliance	Notable minority
Overall willingness to continue using	High

Nurses reported a clear increase in their confidence in recognising and managing deterioration after using the system, which is significant given how heavily home care depends on the individual nurse's judgement and self-assurance. They found the system useful and reasonably easy to use, and most expressed willingness to continue using it. At the same time, a notable minority raised concerns that echo the wider literature, principally the burden of alerts and the risk of becoming over-reliant on the technology at the expense of their own clinical skills. These concerns did not outweigh the overall positive reception, but they are important, because they point to real risks that must be managed if the system is to be used well over the long term.

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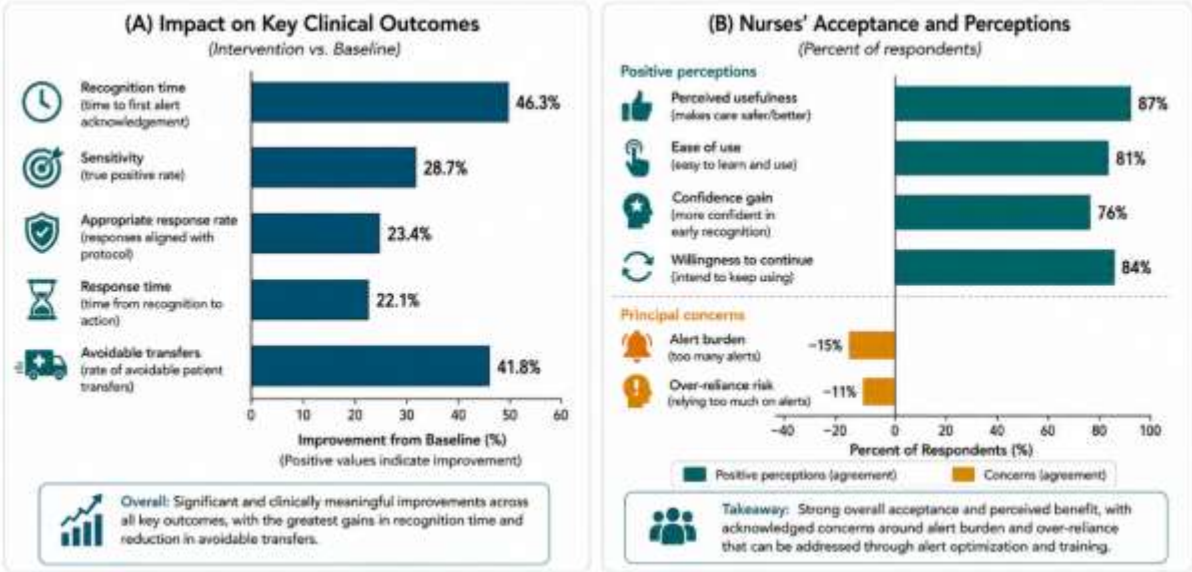

Figure 4. Overall impact of the AI-assisted early warning system.

6. DISCUSSION

The findings of this study make a coherent and encouraging case that an AI-assisted early warning system can meaningfully improve the recognition and management of clinical deterioration by nurses in home healthcare, while also offering a realistic picture of the concerns that accompany such technology. The central result is that the system helped nurses catch deterioration earlier and more accurately. The near-halving of the time to recognition and the sharp fall in missed events are not marginal improvements but substantial ones, and they matter enormously in the home setting, where the isolation of the nurse and the distance from emergency help make early recognition both harder and more critical than in a hospital. By providing an intelligent additional layer of vigilance, the system appears to have compensated, at least in part, for the very support structures that home care lacks, which is precisely where its value was expected to lie.

Equally important is that the improved recognition translated into improved action and better outcomes. It would have been possible, in principle, for a system to improve detection without improving care, if nurses recognised deterioration earlier but did not respond better, but this was not what happened. Management responses became more appropriate and faster, and, most tellingly, avoidable hospital transfers fell. This last finding deserves emphasis, because reducing avoidable transfers benefits patients, who are spared the disruption and risks of hospital admission and can be cared for in their preferred setting, and also relieves pressure on hospital resources. That earlier, better home-based management could keep some deteriorating patients safely at home speaks directly to one of the central promises of home healthcare, and it suggests that the technology strengthens rather than merely supplements the model of care.

The maintenance of specificity alongside improved sensitivity is a subtle but significant result that deserves attention. A common failing of alerting systems is that they achieve greater sensitivity only by generating many false alarms, which quickly leads to alert fatigue and undermines the whole system as clinicians learn to ignore the alerts. That specificity was preserved, and even slightly improved, indicates that the system helped nurses find more genuine deterioration without drowning them in false positives, which is essential to its practical usefulness and to its long-term acceptance. This balance between catching true events

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and avoiding false alarms is one of the hardest things for such systems to achieve, and its apparent success here is a genuinely positive sign.

The findings on nurses' confidence and acceptance are important because they bear on whether the benefits can be sustained. The increase in nurses' confidence is valuable in its own right, given how much home care rests on the individual nurse's assurance in their own judgement, and the generally positive reception suggests the system was seen as a helpful tool rather than an imposition. At the same time, the concerns nurses raised about alert burden and over-reliance are neither surprising nor trivial, and they align closely with the wider literature on clinical technology. The concern about over-reliance is particularly worth taking seriously, because there is a real risk that nurses who come to depend on an AI system may allow their own vigilance and skills to atrophy, which would be dangerous if the system were ever unavailable or wrong. This reinforces the principle, central to the design of the intervention, that the system should support and not replace clinical judgement, and it implies that sustaining the benefits will require ongoing attention to keeping nurses' own skills sharp and to managing the volume and quality of alerts so that the system remains a help rather than a burden.

Several limitations must be acknowledged honestly. The study used a quasi-experimental rather than a fully randomised design, which, while appropriate and practical for evaluating an intervention in a real clinical service, leaves more room than a randomised trial for unmeasured factors to influence the results, so the findings, though strengthened by the comparison group and the before-and-after design, should be interpreted with appropriate caution. The study was conducted in a specific setting, home healthcare in Doha, Qatar, and the extent to which the findings generalise to other settings with different patient populations, healthcare systems, and nursing practices cannot be assumed and would need to be tested. The evaluation covered a defined study period, and the longer-term effects of the system, including whether the benefits are sustained and whether concerns such as over-reliance or alert fatigue grow over time, remain to be established. Finally, the study assessed the system as used by nurses and did not isolate the technical performance of the AI itself from the way nurses used it, so the results reflect the combined human-plus-technology system rather than the algorithm alone, which is arguably the more relevant outcome for practice but which does mean the findings are about the intervention as a whole.

These limitations point toward clear directions for future work. Larger studies, ideally including randomised designs where feasible, would strengthen the evidence and allow more confident causal attribution. Evaluation across diverse settings would establish how far the benefits generalise beyond the specific context studied here. Longer-term follow-up would reveal whether the improvements are sustained and whether the concerns nurses raised materialise into real problems over time, which is essential for understanding the durability of the benefit. Further work could also examine how best to design the alerts and the training to minimise alert burden and guard against over-reliance, and could explore the cost-effectiveness of the system, given the reduction in avoidable transfers suggests it may offer economic as well as clinical benefits. The present study provides a strong foundation and a compelling rationale for these further investigations.

7. CONCLUSION

This study evaluated the effectiveness of an artificial intelligence-assisted early warning system on nurses' recognition and management of clinical deterioration among patients receiving home healthcare in Doha, Qatar, and the findings were clear and encouraging. Following the

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introduction of the system, nurses in the intervention group recognised deterioration substantially earlier and more accurately than before and than the comparison group, roughly halving the time to recognition and sharply reducing the proportion of missed events, and doing so without any loss of specificity. This improved recognition translated into better management, with more appropriate and faster responses and, notably, a reduction in avoidable hospital transfers, indicating that earlier and better home-based intervention allowed some deteriorating patients to be safely cared for at home who might otherwise have been admitted. Nurses reported increased confidence and broadly positive acceptance of the system, while also raising legitimate concerns about alert burden and the risk of over-reliance.

The central contribution of this work is to provide real-world evidence, from a genuine home healthcare setting, that an AI-assisted early warning system can strengthen the safety of home care by helping nurses detect and respond to deterioration earlier and more effectively. This matters because the home setting, with its isolated nurses and its distance from emergency help, is precisely where earlier recognition is both hardest and most consequential, and where an intelligent additional layer of vigilance can do the most good. At the same time, the study underscores that the technology is not a substitute for nursing skill and judgement but a support for it, and that realising its benefits sustainably will require managing alert burden, guarding against over-reliance, and keeping nurses' own competencies sharp. With larger and longer studies across diverse settings to confirm and extend these findings, AI-assisted early warning systems of the kind evaluated here hold real promise as a means of making home healthcare safer, allowing more patients to receive high-quality, responsive care in the comfort of their own homes.

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