Saudi J. Med. Pub. Health **Vol. 1,** No. 2, pp 1967-1975 (2024)

Saudi Journal of Medicine and Public Health

https://saudijmph.com/index.php/pub

https://doi.org/10.64483/202412557

Ambient Intelligence and Sensor Technology in Nursing Care: A Review of Applications for Fall Prevention, Elopement Management, and Subtle Change Detection

Jawaher Aied Alrashidy [1] , Nader Hussain Alahmadi [1] , Ogab Owaied Mohammad Almutairi [1] , Majed Snid Alsehly [1] , Massad Mubark Alsobhi [1] , Najat Salem Reja Alblwi [2] , Eman Mosa Alamri [2] , Ibtisam Ali Al johni [3] , Muslih Saleh Aljohani [4] , Khaled Abdullah Ali Al-Ghammas [5] , Ahmad Salim S Alrashedi [6] , Abdulaziz Obidallah Salma Alahmada [4] , Aisha Awad Alanazi [6]

(1) Madinah Health Cluster, Ministry of Health, Saudi Arabia,
(2) branch in Medina - Commitment management, Ministry of Health, Saudi Arabia,
(3) Health Cluster - Agreements and Community Partnerships, Ministry of Health, Saudi Arabia,
(4) Defense Health Center, Ministry of Health, Saudi Arabia,
(5) Qassim Health Cluster, Ministry of Health, Saudi Arabia,
(6) Khyber General Hospital, Ministry of Health, Saudi Arabia

Abstract

Background: Patient safety incidents like falls and undetected clinical deterioration are ongoing challenges in healthcare, leading to increased morbidity and costs. Traditional methods, such as nurse call systems, are reactive and resource-heavy. Ambient intelligent (AmI) systems, using unobtrusive sensors and AI, enable continuous monitoring and proactive intervention.
Aim: This narrative review aims to synthesize and critically analyze the current state of evidence regarding ambient sensor technologies in nursing care, with a focused examination of their application in fall prevention, elopement management, and the detection of subtle physiological or behavioral changes.
Methods: A comprehensive literature search was conducted using PubMed, CINAHL, IEEE Xplore, and ACM Digital Library for peer-reviewed articles (2010-2024).
Results: Evidence shows that ambient systems have over 90% accuracy in detecting falls and alerting elopements in controlled environments. Although predictive analytics for fall prevention using movement patterns are developing, data on their real-world clinical effectiveness is scarce. There are ongoing concerns about data privacy, algorithmic bias, the loss of human interaction, and the ethics of constant surveillance, especially for vulnerable groups like dementia patients.
Conclusion: Ambient intelligence can significantly improve nursing care and patient safety, but its successful integration requires a balanced, evidence-based, and ethical approach. Key factors include co-design with end-users, robust privacy-by-design frameworks, thoughtful implementation to support nursing judgment, and further high-quality research to prove its clinical and economic benefits.
Keywords: Ambient Intelligence; Patient Safety; Nursing Care; Fall Prevention; Ethical Surveillance

Introduction

Patient safety constitutes a fundamental pillar of quality healthcare, yet preventable adverse events remain a formidable challenge. In hospitals and long-term care settings, incidents such as falls and elopement (unauthorized departure) are prevalent, leading to patient injury, psychological distress, increased length of stay, and substantial financial burden (Oliver et al., 2010; Khaletabad et al., 2023). Concurrently, the early detection of subtle clinical deterioration—manifested in changes in mobility, sleep patterns, or behavior—is critical for preventing cascading complications, but often eludes traditional intermittent monitoring (Downey et al., 2018). Nursing staff, operating under constant pressure of high workloads and staffing shortages, are tasked with the vigilant surveillance necessary to prevent these events, primarily through periodic rounding and reliance on patient-activated call systems. These methods are inherently reactive, labour-intensive, and can be ineffective for cognitively impaired patients who may not call for help (Dykes et al., 2009).

The emergence of Ambient Intelligence (AmI) and advanced sensor technology heralds a potential transformation in this landscape. AmI refers to electronic environments that are sensitive and responsive to the presence of people, operating unobtrusively in the background (Aarts & de Ruyter, 2009). In healthcare, this translates to networks of non-contact, "passive" sensors—such as depth-sensing cameras (e.g., Microsoft Kinect), radar, thermal arrays, bed/chair load cells, floor-based vibration sensors, and passive infrared (PIR) motion sensors—integrated with machine learning algorithms to interpret activities and patterns (Phull et al., 2016). Unlike wearable devices (pendants, smartwatches),

*Corresponding author e-mail: Jaalrashidy@moh.gov.sa (Jawaher Aied Alrashidy).
Receive Date: 21 December 2024, Revise Date: 30 December 2024, Accept Date: 31 December 2024

which require patient compliance and can be stigmatizing or removed, ambient systems aim for seamless, continuous monitoring without direct patient interaction.

This narrative review synthesizes the current evidence on the application of ambient sensor technology in nursing care, focusing on three critical safety domains: fall prevention (and detection), elopement management, and the detection of subtle physiological/behavioral changes. It moves beyond a mere technical appraisal to critically analyze the impact of these systems on nursing workflow, their acceptance by patients and staff, and the profound ethical and privacy dilemmas they introduce. As healthcare stands on the cusp of this surveillance-augmented era, a balanced understanding of its promises and perils is essential for nurses, technologists, and policymakers alike.

The Technological Ecosystem of Ambient Monitoring

Ambient monitoring in clinical settings is not defined by a single technology but by a diverse and evolving ecosystem of sensing modalities, each with distinct operational principles, strengths, and inherent limitations. A clear understanding of this technological taxonomy is foundational for evaluating its appropriate application, integration challenges, and overall efficacy in supporting nursing care and patient safety (Queirós et al., 2017).

Vision-based sensors constitute a primary category, encompassing traditional RGB cameras, depth-sensing cameras (e.g., Microsoft Azure Kinect), and thermal imaging systems. Depth sensors are particularly significant for healthcare applications, as they generate a three-dimensional point cloud or skeletal model of an individual, enabling sophisticated analysis of posture, gait, and complex movements without capturing identifiable facial features, thus offering a valuable compromise between data richness and visual privacy (Stone & Skubic, 2014). Thermal cameras, which detect infrared radiation (body heat), provide the capability for presence detection and basic activity monitoring even in complete darkness, further preserving patient anonymity by producing only a thermal silhouette. These technologies are especially effective for applications requiring detailed kinematic analysis, such as fall detection and quality-of-movement assessment.

A distinct and increasingly prominent category is that of radio frequency (RF) and radar sensors, including Doppler radar, ultra-wideband (UWB) radar, and emerging Wi-Fi-based sensing techniques. These systems operate by emitting radio waves and analyzing their reflections. A key advantage is their ability to detect subtle physiological motions, such as the micromovements of the chest wall for non-contact respiratory and even heart rate monitoring via ballistocardiography (Yen et al., 2023). Furthermore, radar can classify activities based on their unique "micro-Doppler" signatures—the frequency shifts caused by motion—allowing it to distinguish, for instance, between a fall and a rapid sit-down. Crucially, radar sensors can operate through non-metallic obstructions like clothing and blankets and generate no visual imagery, thereby presenting a strong privacy-preserving alternative to optical systems.

Environmental and pressure-based sensors represent some of the most established and widely deployed technologies in clinical environments. This category includes piezoelectric floor mats, bed- and chair-integrated load cells (exit alarms), fiber-optic mats, and vibration sensors. Their primary use has been as simple, reliable alert systems to notify staff when a patient at high risk for falls attempts to rise from a bed or chair (Chen et al., 2020). However, their application is becoming more advanced; for example, grids of pressure-sensitive floor tiles can be used to continuously map gait parameters—such as stride length, velocity, and step symmetry—as a patient walks naturally. These quantitative gait metrics, captured unobtrusively during activities of daily living, serve as powerful, objective indicators of mobility decline and future fall risk (Jeon & Cho, 2020).

While acoustic sensors (microphone arrays) have been explored for detecting specific audio events like a cry for help or the impact sound of a fall, their deployment is severely limited by profound and legitimate privacy concerns, rendering them unsuitable for most continuous monitoring scenarios (Hafeez et al., 2023). The trajectory of technological advancement is instead moving decisively toward multimodal sensor fusion. The most robust and context-aware ambient systems integrate data streams from two or more complementary sensor types—for example, combining the detailed skeletal tracking of a depth camera with the through-obstruction sensing of radar and the precise weight distribution data from a pressure-sensitive floor (Nweke et al., 2018). This fusion approach mitigates the weaknesses of any single modality, dramatically improves classification accuracy, reduces the incidence of false alarms, and provides a much richer, more reliable contextual understanding of patient activities and states (Bharti et al., 2018). Ultimately, the intelligence of any ambient monitoring system resides not merely in its hardware but in the sophisticated machine learning and data fusion algorithms that process these heterogeneous raw data streams to accurately classify activities, predict risks, and generate clinically meaningful, actionable alerts for nursing staff (Table 1). Figure 1 illustrates major sensor modalities—including depth-sensing cameras, radar-based sensors, pressure and load sensors, thermal imaging, and passive infrared motion detectors—and their integration through multimodal sensor fusion and artificial intelligence algorithms.

Saudi Journal of Medicine and Public Health

https://doi.org/10.64483/202412557

Table 1: Taxonomy of Ambient Sensor Technologies for Patient Monitoring

Sensor Type	Primary Data	Key Applications	Strengths	Limitations & Privacy Considerations
Depth-Sensing Camera	3D skeleton joints, point cloud	Fall detection/prevention, gait analysis, activity recognition.	High spatial accuracy, preserves facial anonymity, detailed movement data.	Limited field of view, requires line-of-sight, may be perceived as intrusive.
Radar (Doppler/UWB)	Micro-movement, velocity, distance	Respiration/heart rate monitoring, fall detection, presence sensing.	Works through walls/blankets, high privacy (no visual data), robust in darkness.	Lower spatial resolution than cameras, complex data interpretation.
Pressure Sensors (Mats, Load Cells)	Force, weight distribution	Bed/chair exit alerts, restlessness monitoring, basic gait analysis on floors.	Simple, low-cost, non-visual, well-established for exit alerts.	Limited to specific location, can be bypassed, provides limited contextual data.
Thermal Camera	Heat signature (temperature map)	Presence detection, fall detection, basic activity in darkness.	Works in no light, protects visual identity.	Lower resolution, sensitive to environmental temperature, cannot discern fine details.
Passive Infrared (PIR)	Motion (infradiation change)	Room occupancy, gross movement detection.	Very low cost, low power, simple.	No detail on activity type, high false alarms, no identification.
Multimodal Fusion	Combined data streams from ≥2 types	Comprehensive monitoring, reduced false alarms, predictive analytics.	Highest accuracy and reliability, rich contextual data.	High cost and complexity, integrated privacy challenges.

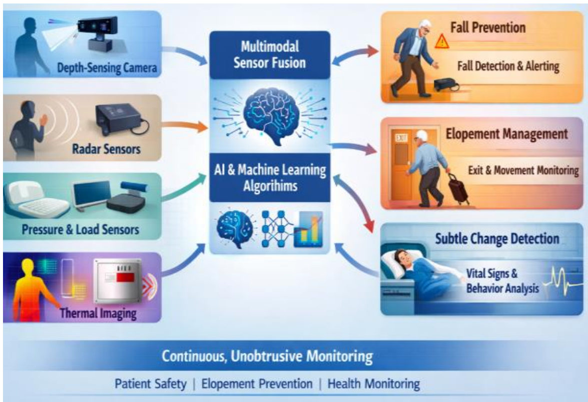

Figure 1. Technological Ecosystem of Ambient Intelligence in Nursing Care

Fall Prevention and Detection

Falls persist as one of the most prevalent and consequential adverse events across healthcare settings, contributing to patient injury, extended hospital stays, and high financial costs. Ambient technology confronts this challenge through a dual-strategy approach, targeting both the immediate aftermath of a fall and its antecedent risk factors. The first strategy, **fall detection**, aims to automatically identify a fall event in real-time and summon assistance, thereby minimizing the dangerous "long-lie" period associated with complications (Oliver et al., 2010). While early solutions depended on wearable pendants, contemporary ambient systems utilizing depth-sensing cameras and radar have demonstrated superior technical performance in controlled environments. Depth cameras can analyze the velocity of a person's center of mass and their final posture to differentiate a true fall from controlled activities like sitting or lying, achieving reported sensitivity and specificity rates often above 95% (Kepski & Kwolek, 2014; Stone & Skubic, 2014). Similarly, radar systems identify the distinct micro-Doppler signature of a rapid, involuntary descent, offering comparable accuracy without requiring line-of-sight (Yen et al., 2023). This capability represents a critical advancement over traditional bed or chair exit alarms, which only signal an attempt to rise, not the fall itself.

The second, more proactive strategy is **fall risk assessment and prevention**. Here, ambient systems shift from reactive alerting to predictive analytics. By continuously and unobtrusively

*Corresponding author e-mail: Jaalrashidy@moh.gov.sa (Jawaher Aied Alrashidy).
Receive Date: 21 December 2024, Revise Date: 30 December 2024, Accept Date: 31 December 2024

monitoring natural gait parameters—such as speed, stride length, variability, and symmetry—during a patient's daily ambulation, these systems can identify degradations in mobility that serve as biomarkers for heightened fall risk (Van Ancum et al., 2019). Research indicates that gait metrics extracted from depth sensor data correlate strongly with standardized clinical assessments and possess predictive validity for future falls in older adult populations (Galna et al., 2013). In a clinical workflow, such a system could alert nursing staff to a patient's declining mobility, prompting targeted interventions like a medication review, physical therapy consultation, or environmental modification *before* a fall occurs, embodying a paradigm shift toward proactive, data-driven risk mitigation (Moon et al., 2016).

The **impact on nursing workflow** associated with these applications is complex. Effective fall detection can theoretically reduce response times and improve post-fall outcomes, while predictive analytics could enable nurses to strategically prioritize care for high-risk individuals. However, the evidence for tangible reductions in overall fall rates within complex, real-world clinical environments remains equivocal, highlighting a need for more robust, large-scale randomized controlled trials (Chen et al., 2020). A paramount challenge is the management of **false alarms**. Systems that generate excessive or inaccurate alerts contribute directly to alarm fatigue, leading to desensitization, increased cognitive load, and workflow disruption, which can utterly undermine the technology's purported benefits (Sendelbach & Funk, 2013). Consequently, the development of multimodal sensing architectures and more sophisticated, context-aware algorithms to minimize false positives is an active and critical area of technological refinement.

Elopement Management in Cognitively Impaired Populations

Elopement, or unsupervised wandering, constitutes a serious safety risk for patients with dementia or cognitive impairment in hospitals and long-term care facilities, exposing them to potential injury, environmental hazards, and fatal outcomes. Ambient technologies offer a continuous monitoring framework to manage this risk. Core systems typically employ a layered technological approach, combining passive infrared (PIR) or depth sensors to monitor movement patterns within a room or ward with door-mounted sensors—such as radio-frequency identification (RFID), Bluetooth Low Energy (BLE) beacons, or magnetic contacts—to detect unauthorized exits (Niemeijer et al., 2015). When a patient identified as high-risk approaches a secure egress point or enters an unsupervised zone, the system triggers an immediate alert to nursing staff via pagers or central station consoles. More advanced implementations utilize indoor positioning systems (IPS) with ultra-wideband (UWB) or BLE beacons to provide real-time location tracking throughout a facility, drastically reducing search time if elopement occurs.

Moving beyond basic perimeter security, ambient intelligence enables **pattern analysis and preventative intervention**. By analyzing movement data over time, these systems can identify precursors to elopement attempts, such as repetitive pacing, "lapping" behaviors, or increased agitation and lingering near exits (Sokolov et al., 2020). Detecting these patterns provides nursing staff with early warnings of patient restlessness or unmet needs—such as pain, thirst, or the need for toileting—allowing for proactive, person-centered interventions. A nurse, thus alerted, can engage the patient with distraction, offer a drink, or assist with bathroom use, addressing the likely root cause of the behavior rather than merely responding to its dangerous consequence. This approach aligns strongly with ethical, non-pharmacological models of dementia care that prioritize individual needs and autonomy.

Inevitably, the deployment of tracking technology for elopement management engenders significant **ethical tensions**, centering on the classic dilemma of safety versus autonomy. While enhancing physical security, pervasive monitoring can be perceived as overly restrictive, infantilizing, and an infringement on personal liberty (Niemeijer et al., 2015). The guiding ethical principle must be one of proportionality: the technology should act as an enabler of safe freedom, not as a digital form of restraint. Critical to ethical implementation is involving patients (to the extent of their capacity) and their families in decision-making processes, ensuring transparency about the technology's function, and rigorously evaluating whether its use constitutes the least restrictive option available to ensure safety (Wangmo et al., 2019).

Detection of Subtle Physiological and Behavioral Changes

The most transformative potential of ambient intelligence may lie in its capacity to detect subtle, subclinical changes in a patient's condition, shifting monitoring from a focus on discrete adverse events to the continuous interpretation of integrated health signatures. In the realm of **physiological monitoring**, non-contact sensors offer groundbreaking capabilities. Doppler radar can detect micromovements of the chest wall to derive respiratory rate and, through ballistocardiographic analysis, even estimate heart rate (Yen et al., 2023). Thermal cameras can similarly monitor breathing by detecting temperature fluctuations at the nostrils. This continuous, unobtrusive collection of vital signs could provide an early warning system for conditions like evolving sepsis, opioid-induced respiratory depression, or decompensating heart failure, often identifying trends hours before they manifest in dramatic changes captured during intermittent manual checks (Downey et al., 2018).

Equally powerful is the capacity for **behavioral and activity profiling**. By establishing a longitudinal baseline of an individual's normal patterns—including sleep-wake cycles, time distribution between bed and chair, ambulation levels, and frequency of bathroom visits—ambient systems can identify statistically significant deviations that may signal decline. For example, increased nighttime restlessness and sleep fragmentation are recognized biomarkers for delirium, pain, or underlying infection (Matarese et al., 2015). A marked reduction in overall activity or social withdrawal may indicate depression or clinical worsening. In postoperative settings, a decline in ambulation frequency or distance, as measured by floor sensors, has been correlated with a higher risk of complications (Juita et al., 2023). These subtle behavioral biomarkers, often invisible to periodic nursing checks, provide an objective, data-driven signal that can prompt earlier clinical investigation (Pederson et al., 2020).

This application most directly **augments the holistic nursing assessment**, providing objective data streams to complement and inform clinical intuition. It can assist nurses in triaging attention, offering quantifiable evidence of recovery or deterioration. However, it simultaneously raises a critical pedagogical and philosophical question: could an over-reliance on constant algorithmic data interpretation inadvertently lead to the **deskilling** of nurses, diminishing the value placed on hands-on, holistic assessment and the nuanced, empathetic observation that defines expert nursing practice (Iwuchukwu et al., 2023)? The ultimate challenge is to ensure these technologies serve as tools that enhance, rather than replace, the irreplaceable human elements of clinical judgment and therapeutic presence (Table 2). Figure 2 highlights three core domains: (1) fall prevention and detection through gait analysis and postural monitoring, (2) elopement management via movement pattern recognition and exit monitoring in cognitively impaired patients, and (3) detection of subtle physiological and behavioral changes using non-contact vital sign monitoring and longitudinal activity profiling.

Impact on Nursing Workflow, Acceptance, and the Nurse-Patient Relationship

The successful integration of ambient technology into clinical settings depends far less on its technical sophistication than on its harmonious adoption within the complex, human-centric ecosystem of care. A critical dimension is its impact on nursing workflow and clinical decision-making. Proponents argue that Ambient Intelligence (AmI) can alleviate the burdensome task of continuous visual surveillance, theoretically freeing nurses to dedicate more time to higher-value, compassionate care activities (Phillips et al., 2017).

Table 2: Synthesis of Benefits, Challenges, and Unresolved Questions by Application Domain

Domain	Potential Benefits	Technical & Clinical Challenges	Workflow & Human Factors	Key Ethical & Privacy Questions
Fall Prevention/Detection	Reduced fall-related injuries; shorter lie times; proactive risk assessment; objective gait data.	High false alarm rates; algorithm performance in cluttered rooms; proving reduction in fall rates in RCTs.	Alarm fatigue; integration into rapid response protocols; changing nurse rounding behavior.	Is predictive risk assessment a form of pre-emptive restriction? Who acts on a "high risk" flag?
Elopement Management	Enhanced physical safety; reduced use of physical/chemical restraints; insight into wandering patterns.	Balancing sensitivity (catch all exits) vs. specificity (avoid false alarms); indoor positioning accuracy.	Alert integration without causing panic; enabling preventive, non-technical interventions.	Does tracking infringe on autonomy & dignity? Is it the least restrictive option? Informed consent in dementia.
Subtle Change Detection	Early warning of clinical deterioration; objective behavioral baselines; continuous, unobtrusive monitoring.	Defining clinically significant deviations; data overload; validating biomarkers against outcomes.	Interpreting data streams; avoiding diagnostic over-reliance; integrating alerts into clinical reasoning.	What constitutes "normal" behavior? Risk of profiling & bias; privacy of intimate behavioral data.

Saudi Journal of Medicine and Public Health
https://saudijmph.com/index.php/pub
https://doi.org/10.64483/202412557

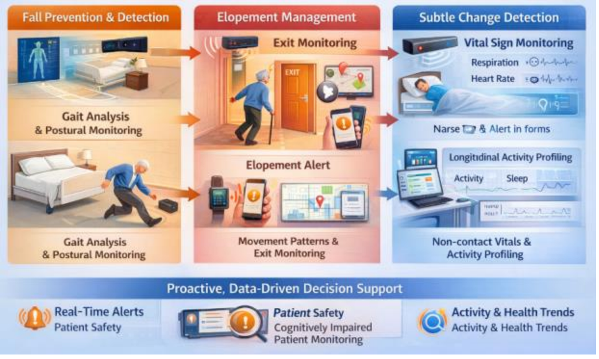

Figure 2. Clinical Applications of Ambient Sensor Technologies for Patient Safety

When functioning optimally, these systems can provide actionable alerts that help nurses prioritize attention and intervene more rapidly. However, this potential is readily undermined by poorly designed implementations. Systems plagued by high rates of false alarms can disrupt workflows, contribute to cognitive overload, and foster alarm fatigue, ultimately increasing rather than decreasing nursing burden (Sendelbach & Funk, 2013). Therefore, the utility of AmI hinges on the delivery of actionable intelligence—alerts that are not only timely and accurate but are integrated with clear clinical response protocols. Beyond mere alert response, effective implementation requires training nurses to interpret longitudinal data trends, ensuring the technology augments and informs clinical judgment rather than seeking to replace it (Ali et al., 2022).

Parallel to workflow integration is the challenge of patient and staff acceptance, a multifaceted issue rooted in perception and trust. For patients, particularly older adults or those with cognitive impairments, ambient monitoring can raise significant privacy concerns, a perceived loss of autonomy, and the psychological discomfort of feeling perpetually observed (Courtney et al., 2008). Transparent communication about the purpose, data practices, and benefits of the technology is therefore paramount. For nursing staff, acceptance is contingent on perceived usefulness, ease of use, and, fundamentally, trust in the system's reliability. Resistance may emerge from fears that the technology monitors their own performance, concerns about increased liability, or a philosophical skepticism that algorithmic surveillance can substitute for the nuanced "caring gaze" of the nurse (Berridge et al., 2019). To navigate these barriers, involving frontline nurses as co-designers in the development and implementation process is crucial for creating tools that are not only usable but also trusted and aligned with clinical realities.

This skepticism touches upon a profound existential concern for the nursing profession: the potential erosion of therapeutic presence and the "caring gaze." Nursing surveillance is not a mechanistic data-collection exercise; it is a holistic, relational process involving presence, observation, and therapeutic engagement (Tanner, 2006). A significant risk posed by ambient monitoring is that an over-reliance on sensor-derived data could lead to reduced direct patient contact, as nurses might be tempted to substitute physical rounds with dashboard checks. This could result in missing subtle, yet critical, nonverbal cues of pain, anxiety, or emotional distress that no sensor can currently detect. The central challenge, therefore, is to strategically position ambient intelligence as a tool that *enables* more meaningful human interaction by offloading routine mechanistic monitoring, not as a technology that replaces the essential human connection at the heart of nursing care.

Ethical and Privacy Implications

The pervasive, continuous nature of ambient monitoring inherently raises deep ethical and legal questions that demand proactive and rigorous governance. At the forefront are concerns of privacy, dignity, and data governance. Continuous monitoring, even with privacy-preserving technologies like depth-sensing cameras that generate skeleton avatars, constitutes an intrusion into spaces where patients are at their most vulnerable. The mere psychological awareness of being watched can impact a patient's sense of dignity and well-being (Wangmo et al., 2019). Addressing this requires the embeddedment of privacy-by-design principles: data minimization, end-to-end encryption, strict access controls, and transparent policies on data retention and deletion. Furthermore, respecting patient autonomy necessitates robust informed consent processes that clearly explain the scope of monitoring and, where clinically feasible, provide a meaningful right to opt-out (Mittelstadt, 2017).

The principle of informed consent becomes exceptionally complex in vulnerable populations, such as patients with dementia or acute confusion. Ethical dilemmas arise regarding whether consent can be legitimately provided by family proxies, or if such monitoring should be considered a default, necessary safety feature in certain care units, analogous to other protective measures (Niemeijer et al., 2015). These questions lack universal answers and underscore the need for ongoing ethical deliberation, possibly culminating in new legal and policy frameworks specific to digital monitoring in care. A further, systemic ethical risk is that of algorithmic bias and injustice. Machine learning models powering these systems are trained on datasets that may underrepresent diverse patient populations in terms of body habitus, skin tone (affecting thermal/visual

*Corresponding author e-mail: Jaalrashidy@moh.gov.sa (Jawaher Aied Alrashidy).
Receive Date: 21 December 2024, Revise Date: 30 December 2024, Accept Date: 31 December 2024

sensors), gait patterns, or cultural behavioral norms. This can lead to reduced accuracy and reliability for marginalized groups, potentially exacerbating existing health disparities—a risk that makes rigorous bias testing across diverse cohorts a non-negotiable step in development and validation (Obermeyer et al., 2019).

Finally, the ambient monitoring infrastructure introduces the danger of function creep and the normalization of surveillance. Data collected for the primary purpose of enhancing patient safety (e.g., fall prevention) could be repurposed for secondary, more problematic uses, such as monitoring staff productivity, assessing patient "compliance" with care plans, or informing insurance and liability determinations (Lyon, 2018). Without clear, transparent, and enforceable governance structures that strictly define data use parameters, this "creep" is a significant threat. Such governance is essential not only to protect individual rights but also to guard against the gradual normalization of pervasive surveillance as an unexamined standard within caring environments, thereby preserving the fundamental trust that underpins the therapeutic relationship.

Conclusion

Ambient intelligence and sensor technology present a powerful, double-edged sword for nursing care. The evidence reviewed indicates strong technical potential for enhancing patient safety in the domains of fall prevention, elopement management, and early detection of deterioration. These systems can provide objective, continuous data that complements nursing judgment and may alleviate some burdens of routine surveillance.

However, the path to successful, ethical integration is fraught with challenges. The current evidence base, while promising, often consists of small-scale studies with limited generalizability; more robust, real-world clinical trials are urgently needed to demonstrate impact on hard outcomes like fall rates, code blue events, and patient length of stay. Beyond efficacy, the human and ethical dimensions are paramount. The risk of eroding the nurse-patient relationship, infringing on patient privacy and autonomy, and introducing algorithmic bias must be actively managed, not as an afterthought, but as a core component of design and implementation.

The future of ambient intelligence in nursing should not be one of replacement, but of augmentation. The goal must be to create "intelligent care spaces" where technology works silently in the background to empower nurses with timely insights, allowing them to redirect their time and expertise from mechanistic vigilance to the empathetic, human-centered care that defines the nursing profession. Achieving this vision requires a collaborative, multidisciplinary approach involving nurses, patients, ethicists, engineers, and policymakers. It demands rigorous evidence, thoughtful design centered on human values, and ongoing democratic dialogue about the kind of caring environments we wish to build in an increasingly technological age.

References

1. Aarts, E., & De Ruyter, B. (2009). New research perspectives on ambient intelligence. *Journal of Ambient Intelligence and Smart Environments*, *1*(1), 5-14. https://doi.org/10.3233/AIS-2009-0001
2. Ali, S., Kleib, M., Paul, P., Petrovskaya, O., & Kennedy, M. (2022). Compassionate nursing care and the use of digital health technologies: a scoping review. *International Journal of Nursing Studies*, *127*, 104161. https://doi.org/10.1016/j.ijnurstu.2021.104161
3. Berridge, C., Chan, K. T., & Choi, Y. (2019). Sensor-based passive remote monitoring and discordant values: Qualitative study of the experiences of low-income immigrant elders in the United States. *JMIR mHealth and uHealth*, *7*(3), e11516. https://doi.org/10.2196/11516
4. Bharti, P., De, D., Chellappan, S., & Das, S. K. (2018). HuMAn: Complex activity recognition with multi-modal multi-positional body sensing. *IEEE Transactions on Mobile Computing*, *18*(4), 857-870. https://doi.org/10.1109/TMC.2018.2841905
5. Chen, M., Wang, H., Yu, L., Yeung, E. H. K., Luo, J., Tsui, K. L., & Zhao, Y. (2022). A systematic review of wearable sensor-based technologies for fall risk assessment in older adults. *Sensors*, *22*(18), 6752. https://doi.org/10.3390/s22186752
6. Courtney, K. L., Demeris, G., Rantz, M., & Skubic, M. (2008). Needing smart home technologies: the perspectives of older adults in continuing care retirement communities. *Informatics in Primary Care*,16,195–201
7. Downey, C., Randell, R., Brown, J., & Jayne, D. G. (2018). Continuous versus intermittent vital signs monitoring using a wearable, wireless patch in patients admitted to surgical wards: pilot cluster randomized controlled trial. *Journal of medical Internet research*, *20*(12), e10802. https://doi.org/10.2196/10802
8. Dykes, P. C., Carroll, D. L., Hurley, A. C., Benoit, A., & Middleton, B. (2009). Why do patients in acute care hospitals fall? Can falls be prevented?. *JONA: The Journal of Nursing Administration*, *39*(6), 299-304. *DOI:* 10.1097/NNA.0b013e3181a7788a
9. Galna, B., Lord, S., & Rochester, L. (2013). Is gait variability reliable in older adults and Parkinson's disease? Towards an optimal testing protocol. *Gait & posture*, *37*(4), 580-585. https://doi.org/10.1016/j.gaitpost.2012.09.025

10. Hafeez, S., Alotaibi, S. S., Alazeb, A., Al Mudawi, N., & Kim, W. (2023). Multi-sensor-based action monitoring and recognition via hybrid descriptors and logistic regression. *IEEE Access*, *11*, 48145-48157. https://doi.org/10.1109/ACCESS.2023.3275733
11. Iwuchukwu, G., Anttila, M., Lantta, T., Varpula, J., & Ameel, M. (2023). A Mixed-Methods Systematic Review on the Impacts and Implementation of Collaborative Electronic Documentation on Nurse-Patient Relationship. *CIN: Computers, Informatics, Nursing*, 10-1097. *DOI:* 10.1097/CIN.0000000000001263
12. Jeon, E. T., & Cho, H. Y. (2020). A novel method for gait analysis on center of pressure excursion based on a pressure-sensitive mat. *International journal of environmental research and public health*, *17*(21), 7845. https://doi.org/10.3390/ijerph17217845
13. Juita, J., Yona, S., & Maria, R. (2023). The benefits of early mobilization on post-abdominal surgery: a review of literature. *Jurnal Ilmiah Ilmu Keperawatan Indonesia*, *13*(01), 21-33. https://doi.org/10.33221/jiiki.v13i01.2377
14. Kepski, M., & Kwolek, B. (2014, January). Fall detection using ceiling-mounted 3d depth camera. In *2014 International conference on computer vision theory and applications (VISAPP)* (Vol. 2, pp. 640-647). IEEE.
15. Khaletabad, N. A., Radfar, M., Khademi, M., & Khalkhali, H. (2023). Caring Behaviors Inventory-24: translation, cross-cultural adaptation, and psychometric testing for using in nurses and patients. *BMC nursing*, *22*(1), 82. https://doi.org/10.1186/s12912-023-01248-2
16. Lyon, D. (2018). *The culture of surveillance: Watching as a way of life*. John Wiley & Sons.
17. Matarese, M., Ivziku, D., Bartolozzi, F., Piredda, M., & De Marinis, M. G. (2015). Systematic review of fall risk screening tools for older patients in acute hospitals. *Journal of advanced nursing*, *71*(6), 1198-1209. https://doi.org/10.1111/jan.12542
18. Mittelstadt, B. (2017). Ethics of the health-related internet of things: a narrative review. *Ethics and Information Technology*, *19*(3), 157-175. https://doi.org/10.1007/s10676-017-9426-4
19. Moon, Y., Sung, J., An, R., Hernandez, M. E., & Sosnoff, J. J. (2016). Gait variability in people with neurological disorders: A systematic review and meta-analysis. *Human movement science*, *47*, 197-208. https://doi.org/10.1016/j.humov.2016.03.010
20. Niemeijer, A. R., Depla, M. F., Frederiks, B. J., & Hertogh, C. M. (2015). The experiences of people with dementia and intellectual disabilities with surveillance technologies in residential care. *Nursing ethics*, *22*(3), 307-320. https://doi.org/10.1177/0969733014533237
21. Nweke, H. F., Teh, Y. W., Mujtaba, G., Alo, U. R., & Al-garadi, M. A. (2019). Multi-sensor fusion based on multiple classifier systems for human activity identification. *Human-centric Computing and Information Sciences*, *9*(1), 34. https://doi.org/10.1186/s13673-019-0194-5
22. Obermeyer, Z., Powers, B., Vogeli, C., & Mullainathan, S. (2019). Dissecting racial bias in an algorithm used to manage the health of populations. *Science*, *366*(6464), 447-453. https://doi.org/10.1126/science.aax2342
23. Oliver, D., Healey, F., & Haines, T. P. (2010). Preventing falls and fall-related injuries in hospitals. *Clinics in geriatric medicine*, *26*(4), 645-692. https://doi.org/10.1016/j.cger.2010.06.005
24. Pederson, J. L., Padwal, R. S., Warkentin, L. M., Holroyd-Leduc, J. M., Wagg, A., & Khadaroo, R. G. (2020). The impact of delayed mobilization on post-discharge outcomes after emergency abdominal surgery: A prospective cohort study in older patients. *PLoS One*, *15*(11), e0241554. https://doi.org/10.1371/journal.pone.0241554
25. Phillips, L. J., DeRoche, C. B., Rantz, M., Alexander, G. L., Skubic, M., Despins, L., ... & Koopman, R. J. (2017). Using embedded sensors in independent living to predict gait changes and falls. *Western journal of nursing research*, *39*(1), 78-94. https://doi.org/10.1177/0193945916662027
26. Phull, R., Liscano, R., & Mihailidis, A. (2016). Comparative analysis of prominent middleware platforms in the domain of ambient assisted living (AAL) for an older adults with dementia (OAwD) scenario. *Procedia Computer Science*, *83*, 537-544. https://doi.org/10.1016/j.procs.2016.04.252
27. Queirós, A., Dias, A., Silva, A. G., & Rocha, N. P. (2017, July). Ambient assisted living and health-related outcomes—a systematic literature review. In *Informatics* (Vol. 4, No. 3, p. 19). MDPI. https://doi.org/10.3390/informatics4030019
28. Sendelbach, S., & Funk, M. (2013). Alarm fatigue: a patient safety concern. *AACN advanced critical care*, *24*(4), 378-386.

https://doi.org/10.4037/NCI.0b013e3182a903f9

29. Sokolov, A. A., Zeidman, P., Erb, M., Pollick, F. E., Fallgatter, A. J., Ryvlin, P., ... & Pavlova, M. A. (2020). Brain circuits signaling the absence of emotion in body language. *Proceedings of the National Academy of Sciences*, *117*(34), 20868-20873. https://doi.org/10.1073/pnas.2007141117
30. Stone, E. E., & Skubic, M. (2014). Fall detection in homes of older adults using the Microsoft Kinect. *IEEE journal of biomedical and health informatics*, *19*(1), 290-301. https://doi.org/10.1109/JBHI.2014.2312180
31. Tanner, C. A. (2006). Thinking like a nurse: A research-based model of clinical judgment in nursing. *Journal of nursing education*, *45*(6), 204-211. https://doi.org/10.3928/01484834-20060601-04
32. Van Ancum, J. M., van Schooten, K. S., Jonkman, N. H., Huijben, B., van Lummel, R. C., Meskers, C. G., ... & Pijnappels, M. (2019). Gait speed assessed by a 4-m walk test is not representative of daily-life gait speed in community-dwelling adults. *Maturitas*, *121*, 28-34. https://doi.org/10.1016/j.maturitas.2018.12.008
33. Wangmo, T., Lipps, M., Kressig, R. W., & Ienca, M. (2019). Ethical concerns with the use of intelligent assistive technology: findings from a qualitative study with professional stakeholders. *BMC medical ethics*, *20*(1), 98. https://doi.org/10.1186/s12910-019-0437-z
34. Yen, H. T., Kurosawa, M., Kirimoto, T., Hakozaki, Y., Matsui, T., & Sun, G. (2023). Non-contact estimation of cardiac inter-beat interval and heart rate variability using time-frequency domain analysis for CW radar. *IEEE Journal of Electromagnetics, RF and Microwaves in Medicine and Biology*, *7*(4), 457-467. https://doi.org/10.1109/JERM.2023.3326562

.