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AN OVERVIEW, ROLES OF NURSES IN THE USE OF TECHNOLOGICAL PLATFORMS TO IMPROVE PATIENT FLOW

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Abstract:
Growing demand for healthcare services, combined with funding and resource constraints, opens the door for novel technological solutions such as artificial intelligence (AI). The goal of this research is to identify problems with patient flow on healthcare units and match them with potential technological solutions, ultimately developing a model for their integration at the service level. A narrative review was conducted by searching the literature in several electronic databases, including PubMed and Embase, for all relevant studies published in English up to beginning of 2022 that included only human subjects. The review of the literature on nurses using technological platforms to improve patient flow looked at predicting avoidable readmissions, improving care efficiency, optimizing resource allocation, reducing length of stay, and validating existing algorithms for more generalized applications.

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INTRODUCTION:

Patient safety is a subset of healthcare that is defined as the avoidance, prevention, and amelioration of adverse outcomes or injuries caused by health-care processes [1]. Healthcare information technology (HIT) is defined as "the application of information processing involving both computer hardware and software that deals with the storage, retrieval, sharing, and use of health care information, data, and knowledge for communication and decision making". Despite rising costs and demand, healthcare services face a number of challenges in improving the quality and efficiency of care delivery. Internal inefficiencies, such as poor patient flow, have an impact on patient safety, patient/staff satisfaction, and overall care and outcome quality [2]. Mental health is, by definition, a particularly complex field. The rising demand for healthcare, combined with limited resources, has created opportunities for digital and technological solutions such as artificial intelligence (AI) to assist in addressing some of the issues. AI can be used to improve clinical outcomes and patient safety, as well as reduce costs, measure populations, and advance research [3]. Patient flow is defined as 'the ability of healthcare systems to manage patients effectively and with minimal delays as they move through stages of care' [2], with quality and patient satisfaction maintained throughout. As a result, the concept of using patient flow to improve care is gaining traction, "particularly in relation to reductions in patient waiting times for emergency and elective care" [4].

Electronic health records (EHRs) were designed to manage clinical data rather than to engage patients. Patient access to their EHR data via online portals or mobile applications, on the other hand, represents a potential tool for improving patient engagement [1,4]. The potential impact of patient engagement with these platforms will grow in parallel as the landscape expands with the growth of application programming interfaces to increase bidirectional data flow with patients and greater patient access to medical data, such as clinical notes [5].

Currently, approximately 90% of U.S. health care systems and providers provide patients with online portal access to their EHR data, largely supported by the meaningful use program's over $30 billion in financial incentives [5]. Viewing visit summaries, test results, and immunization and allergy lists are common features of online patient portals, as are secure messaging, appointment scheduling, and medication renewals [6]. Despite the presence of a robust patient portal infrastructure in many U.S. health care systems, only 15% to 30% of patients use even a single portal feature, and portal use is largely limited to a specific setting, such as outpatient care in integrated delivery systems [7].

METHODOLOGY:

Narrative review conducted searching literature through several electronic databases such as; PubMed and Embase, for all relevant studies that were published up to 2023, in English language including only human subjects. Most of studies that discussed the technological platforms to improve patient flow were included in this study, future more, references of included studies were searched for more relevant data.

DISCUSSION:

Patient flow management is an essential component of healthcare. Patient flow is defined as 'the ability of healthcare systems to manage patients effectively and with minimal delays as they move through stages of care' [8], while maintaining quality and patient satisfaction throughout. With increasing demand for services versus limited resources, the concept of focusing on patient flow to improve care has gained traction, 'particularly in relation to reductions in patient waiting times for emergency and elective care' [8]. Poor patient flow has been shown to have a negative impact on patients, staff, and overall care quality [9]. The consequences of this include failing to meet the individual needs of patients [10] and overstretching staff, which can lead to an increase in medical errors, readmissions [11], dissatisfaction, prolonged patient length of stay (LOS), and poor health outcomes [12]. On the other hand, efficient patient flow reduces staff workload, improving clinical safety and patient outcomes [8].

NHS Improvement (NHSI) has published a number of tools [12,13] and reports to assist care providers with patient flow, including "SAFER" [15], a practical tool for reducing delays in adult inpatient units, which is commonly used in conjunction with "Red2Green Bed Days" [16], a visual management system used to identify time wasted and LOS during a patient's journey [8]. Despite the fact that these traditional methods are effective, patients on mental health units continue to experience a significant number of red days, with bed occupancy as high as 95%. The average length of stay (LOS) varies greatly between hospitals, even for patients with similar illnesses. According to the 2018 census, the average length of stay in acute mental health units was 36 days [17].

Artificial intelligence (AI) is increasingly being used in healthcare settings, including for patient flow purposes. Medical data has grown in volume and complexity, outstripping the ability of current healthcare systems and professionals to extract all relevant information [18]. Personal health data now includes everything from demographics and medical notes to data generated by wearables and genetic testing. Furthermore, massive amounts of medical data are being digitised, with electronic health records (EHRs) being the most common investment in the global health information technology market [20]. Artificial intelligence (AI) is a disruptive pattern-recognition technology that can perform cognitive functions such as problem-solving, decision-making, and object recognition [21]. Machine Learning (ML), a popular type of AI, learns from data using advanced statistical and probabilistic techniques [22]. Table 1 defines the key terms used in this study. AI has the potential to help us analyze medical data, which could lead to better clinical outcomes, cost savings, and research advancements [23]. The potential for data-driven solutions in mental health is vast. AI has the potential to advance our understanding of the causes of mental illness, improve detection and diagnosis, develop risk-based approaches, improve decisions, and assist in redesigning services to meet the needs of patients [24].

Table 1: Explanation of the key subtypes of Artificial Intelligence.

Machine Learning (ML)	A type of AI in which the system learns and improves with experience without having specified rules. Supervised learning is when the algorithm learns from the training dataset (e.g. Support Vector Machines (SVM), Random Forest (RF)) while unsupervised learning discovers the underlying information and patterns about data (e.g. clustering).
Natural language processing (NLP)	NLP organises unstructured text into structured, valuable text that is interpreted by a machine to extract information. The basic function is to understand and analyse human language, examples include text prediction or information extraction

Some studies focused on developing triage and screening tools [24]. AI has also been applied to enhance our understanding of diseases, improve diagnostic accuracy [25], and even enable new diagnostic methods including novel biomarkers, such as DNA methylation [26]. In the field of prognosis, AI was used to improve accuracy and personalisation of predicting long-term outcomes such as severity [27] relapse, progression [28], and quality of life. For example, Kautzky et al. [29] used 47 clinical and sociodemographic factors to predict treatment resistant depression using RF and 10-fold cross-validation (75% accuracy). Common methods in design of the predictive tools included analysis of EHRs [30] self-reported questionnaires [31] and hospital notes. For example, McCoy et. al. [32] used NLP to extract signs of sentiment from hospital discharge forms and found that it correlated with readmission and mortality risks. Studies on AI in therapy aim to enhance decisions and personalise interventions to maximise likelihood of recovery and allocate resources efficiently. Most widely researched conditions include depression, bipolar disorders, schizophrenia and substance misuse disorders [33]. For example, Koutsouleris et al. [34] used pre-treatment patient data to predict psychosis outcomes after 12 and 52 weeks with 75% and 73.8% accuracy respectively. Researchers were able to predict the risk of symptom persistence, non-adherence to treatment, readmission to hospital, and poor quality of life using factors such as unemployment, poor education, functional deficits, and more. The review on using AI in patient flow revealed that so far, research has been done mostly in the emergency department setting, where AI is often used to predict various patient flow variables such as bed occupancy and rate of readmission [34]. The researchers aimed to utilize AI for efficient resource allocations, preventing avoidable admissions, reducing variation in LOS, and improving discharge [34]. Although some studies have already shown the potential of AI to improve patient flow, those solutions have not been investigated enough for use in mental health inpatient units.

Electronic physician's orders and E-prescribing:

The use of electronic or computer support to enter physician orders, including medication orders, using a computer or mobile device platform is referred to as computerized physician order entry. Originally designed to improve the safety of medication orders, computerized physician order entry systems now allow electronic ordering of tests, procedures, and consultations as well. Computerized physician order entry systems are typically linked to a clinical decision support system (CDS), which serves as an error prevention tool by advising the prescriber on the best drug doses, routes, and frequency of administration. Furthermore, some CPOE systems may prompt the prescriber to any patient allergies, drug-drug or drug-lab interactions, or with sophisticated systems, interventions that should be prescribed based on clinical guideline recommendations (for example, venous thromboembolism prophylaxis). A meta-analysis [35] found that implementing a COPE with clinical decision support resulted in a significant reduction in medication errors (RR:0.46; 95% CI 0.31 to 0.71) and adverse drug reactions (RR: 0.47; 95% CI 0.35 to 0.60). Similarly, studies in community-based outpatient services yielded comparable results in terms of reducing medication errors [36,37]. The use of hard-stops in CPOE systems as a measure of forcing function and error prevention has been studied and found to be effective in changing prescribing errors. The use of hard-stops, on the other hand, resulted in clinically significant treatment delays [37].

Electronic sign-out and hand-off tools & Smart pumps:

Sign-out or "hand-over" communication refers to the process of passing patient-specific information from one caregiver to another, from one team of caregivers to the next, or from caregivers to the patient and family in order to ensure continuity and safety of patient care [35,37]. One of the leading root causes of sentinel events in the United States has been identified as a breakdown in patient information handover [37]. Electronic sign-out applications are tools that can be used independently or in conjunction with an electronic medical record to ensure a structured transfer of patient information during provider handoffs. Two systematic reviews [38,39] evaluating the outcomes of electronic tools supporting physician shift-to-shift handoffs concluded that most studies supported using an electronic tool with an improvement in the handover process, fewer omissions of critical patient information, and reduced handover time, with few low-quality studies assessing patient outcome measures. Both reviews' authors also stated that a significant number of the included studies were poorly designed, and that further evaluation using rigorous study designs is required.

Smart pumps are intravenous infusion pumps that have medication error-prevention software built in. When the infusion setting is set outside of the pre-configured safety limits, this software alerts the operator [39]. The only published randomized controlled trial [40] on the impact of smart pumps on medication safety found no statistical difference when the decision support feature was turned on or off. The authors explained that this was most likely due to healthcare providers' lack of compliance with infusion practices. A systematic review of quasi-experimental studies [41] concluded that smart pumps reduce but do not eliminate programming errors. In addition, hard limits were found to be more effective than soft limits in preventing medication errors. This was explained by the high rate of soft limit override. Further research is required to determine the efficacy of smart pumps in reducing medication errors and improving patient safety.

Community-based remote patient monitoring (telemonitoring) has been shown in studies [41,42] to improve patient outcomes for certain chronic conditions such as heart failure, stroke, COPD, asthma, and hypertension. Patient data management systems (PDMS) are systems that automatically retrieve data from bedside medical equipment (such as a patient monitor, ventilator, and intravenous pump). The data is then summarized and restructured to help healthcare providers interpret it [43]. Recent integration advances have enabled PDMS to be integrated with clinical decision support and the patient's electronic medical record. A systematic review [43] investigated the clinical impact of PDMS and discovered that such systems increased direct patient care time while decreasing charting time. Furthermore, PDMS systems decreased the number of errors (medication errors, ventilator incidents, intravenous incidents, and other incidents). The review also discovered that when a PDMS was integrated with a clinical decision support system, clinical outcomes improved in two studies. According to research, telemedicine technology appears to improve clinical outcomes for certain medical conditions, improve accessibility to healthcare services, and foster patient-physician collaboration. Aside from the limited evidence on PDMS, the impact of telemedicine on patient safety appears to be ambiguous.

Electronic incident reporting systems are web-based systems that enable healthcare providers involved in safety events to report such incidents voluntarily. These systems can be integrated with electronic health records (EHRs) to allow data abstraction and automated detection of adverse events via trigger tools. Electronic incident reporting systems have the potential to standardize reporting structure, standardize incident action workflow, identify serious incidents and trigger events quickly, and automate data entry and analysis. According to published research, healthcare organizations that have switched to an electronic reporting system have seen a significant increase in reporting frequency [44]. Although incident reporting systems may improve clinical processes, there is little evidence that they ultimately reduce medical errors [45].

CONCLUSION:

Electronic incident reporting systems are web-based systems that enable healthcare providers involved in safety events to report such incidents voluntarily. These systems can be integrated with electronic health records (EHRs) to allow data abstraction and automated detection of adverse events via trigger tools. Electronic incident reporting systems have the potential to standardize reporting structure, standardize incident action workflow, identify serious incidents and trigger events quickly, and automate data entry and analysis.

AI has the potential to significantly improve patient flow in three areas: clinical decision making, operational efficiency, and monitoring. While technology is unlikely to reduce the enormous unmet demand for mental health professionals in the near future, AI models can assist with demand prediction, increasing efficient resource allocation, and workforce planning. AI could relieve pressure on mental health services in the near future by streamlining repetitive tasks, giving clinicians more time to spend on direct patient care, and effectively allocating resources.

Numerous studies have been conducted to examine the effects of implementing an electronic medical record on healthcare quality and patient safety, with the majority of studies yielding positive results. However, some studies revealed negative results, which has sparked debate. Future research should incorporate implementation science approaches and address the critical role of clinicians and staff in promoting portal use.

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