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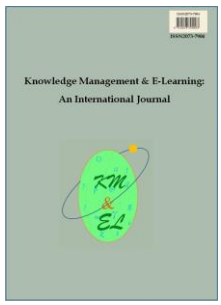

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Alert fatigue and errors caused by technology: A scoping review and introduction to the flow of cognitive processing model

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Abstract: Technologies such as electronic health records (EHRs), embedded clinical decision support systems (CDSS) and computerized physician order entry (CPOE) systems are at the forefront of healthcare's technological revolution. These health information technologies (HIT) pose great promise to improve patient safety, reduce medication errors and increase operational efficiencies in healthcare organizations. However, despite the perceived benefits that these complex technologies offer, their associated risks must not be overlooked or disregarded (Borycki et al., 2012). The objective of this article is to answer the following questions: 1) What is the nature of errors caused by technology (i.e., technology-induced errors) and alert fatigue in healthcare? 2) Is there a relationship between alert fatigue and technology-induced errors? 3) Do organizational strategies exist to address these problems and enhance patient safety? 4) Do technological recommendations exist to improve the current issues surrounding safety? To answer these questions a scoping review following the Arksey and O'Malley (2005) framework was conducted using the CINAHL®, Web of Science®, IEEE *Xplore*® and PubMed® databases. The search focused on English publications only, using the search terms "Alert Fatigue" and "Technology Errors." Articles were iteratively assessed based on the inclusion and exclusion criteria, resulting in an inclusion of 36 articles in the final scoping review. Following this, a thematic analysis was conducted and the findings placed in a data extraction table. The results indicated that while HIT present a significant opportunity to streamline processes and reduce medication errors, there is a critical need to assess them from a patient safety and quality lens. Lastly, a novel conceptual tool was created, the Flow of Cognitive Processing Model. The model provides an iterative perspective and an insightful view into the cognitive realms of

healthcare professionals in their interactions with HIT. By illustrating the complexities of healthcare providers from a humanistic lens, the model could guide HIT design, acquisitions and implementations to reduce alert fatigue and mitigate the introduction of technology-induced errors.

Keywords: Alert fatigue; Errors caused by technology; Technology-induced errors; Patient safety; Healthcare journey; Health informatics; User experience; Journey mapping; Service delivery improvement

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1. Introduction

Fundamental changes are occurring in the healthcare landscape and the practice of medicine is at a pivotal point in its transformation. Healthcare is transitioning from paper-based means of service delivery to electronic. Technologies such as electronic health records (EHRs) with embedded clinical decision support systems (CDSS) and computerized physician order entry (CPOE) systems are at the forefront of this revolution. These health information technologies (HIT) pose great promise to improve patient safety, reduce medication errors and increase operational efficiencies in healthcare organizations. However, despite the perceived benefits that these complex technologies present, their associated risks and unintended consequences must not be overlooked or disregarded (Borycki et al., 2012).

1.1. Technology in medicine and errors caused by technology

Technological distractions remain an important area of concern in health informatics. In medicine the explosion of technology, coupled with a rapid social shift, creates an environment that consistently tempts healthcare workers to surf the internet, respond to e-mails, check social media outlets (Papadakos, 2014). Due to their perceived level of risk, the Emergency Care Research Institute has classified alarms and smart phone distractions as technological hazards (Papadakos, 2014). As healthcare settings are fast paced, chaotic environments characterized by frequent interruptions (Skaugset et al., 2015), the increased reliance on siloed and disparate HIT to access health information must be explored. These operational complexities can introduce other forms of hazards and new types of errors. These new types of errors (i.e., technology-induced errors) can be defined as errors that arise from the design and development of technology (Borycki et al., 2012). Furthermore, technology-induced errors can be caused by the: implementation and customization of a technology, interactions between the operation of a technology, new work processes that evolve from a technology's use (Borycki et al., 2012). As the clinical workflow encompasses both administrative and clinical tasks, all activities (e.g., environments, technologies, people) and organizations involved in delivering care (Tucker, 2019) could be impacted by technology-induced errors.

1.2. Cognitive load theory and alert fatigue

As healthcare professionals adopt electronic service delivery practices through the advent of HIT, they are faced with many challenges. Such challenges include increased patient volumes, technologically imposed clinical and operational workflow disruptions. Technology induced workflow disruptions are often a consequence of institutionally imposed HIT acquisitions or implementations and can disrupt the care delivery workflow. Consequently, healthcare providers (e.g., physicians, nurses, caregivers, health technicians) must often navigate multiple HIT, to access relevant health information to holistically treat patients. The cognitive impacts caused by technologically imposed workflow disruptions, fragmented and siloed HIT must be considered within the context of safety. As technological advancements occur in healthcare, an increased reliance on HIT creates an expectation that healthcare providers use these technologies with extreme hypervigilance (e.g., immediately responding to every alert or notification). "Doctors and medical professionals have always faced interruptions from beepers and phones, and multitasking is simply a fact of life for many. What has changed, doctors say, especially younger ones, is that they face increasing pressure to interact with their devices" (Richtel, 2011). Excessive stimuli from varied technologies are contributors to alert fatigue, which can be defined as the mental state that results when alerts or reminders consume too much time and mental energy (Wan et al., 2020). Alert fatigue can cause physicians to ignore or override both clinically relevant and irrelevant alerts unjustifiably (Wan et al., 2020). Thus, from a user experience (UX) design context, these alerts may not provide relevant or meaningful experiences to their target audience (Levy, 2015).

As there is a limited threshold in which an individual can absorb and respond to stimuli, it is important to refrain from viewing computers and medical providers in the same light. Although physicians and medical professionals are highly efficient and very capable, there are inherent cognitive limitations to information processing and human memory abilities. Organizations must consider health professionals' experience of cognitive load (Sweller, 1988), prior to HIT design and acquisition. Sweller's (1988) cognitive load theory builds on the Atkinson and Shiffrin (1968) model of human information processing and a combination of these theories is presented in Table 1. As

illustrated (Table 1), human memory is categorized into three stages: sensory or short-term memory, working memory, long-term memory.

Table 1
Memory stages (Atkinson & Shiffrin, 1968; Skaugset et al., 2015; Sweller, 1988; Theodore, 2019)

Memory Type	Duration	Capacity	Encoding
Sensory or short- term memory	< 4 seconds	Limited to sensory inputs	Varies per sense
Working memory	< 18 seconds	Limited to 7 items (plus or minus 2 items)	Auditory
Long-term memory	Unlimited	Unlimited	Semantic

As displayed in Table 1 each memory type has a different duration, capacity and encoding mechanism. There are varied limitations of information processing, learning and the ability to recall new information (Skaugset et al., 2015) associated with each memory type. Short term memory is limited to sensory inputs, varies by sense and information is processed for a maximum duration of four seconds. Working memory is limited to auditory memory (e.g., sounds) and a maximum of 18 seconds. In general, working memory allows humans to process seven separate items of varied stimuli concurrently. Long term memory, the final stage in human memory processing has unlimited capacity, duration and semantic coding. As it associates meaning (i.e., logic) to memory processing and storage, long-term memory decays very little with time (The Human Memory, 2020). Furthermore, it is easier to recall and lasts longer than sensory and working memory (The Human Memory, 2020).

The varied memory stages (Table 1), demonstrate the human limitations of information processing with regard to the exposure of varied stimuli. Additionally, Table 1 illustrates that memory saturation could be the potential root cause of alert fatigue and technology-induced errors in a healthcare context. Therefore, in acute care settings from a healthcare provider perspective, alert fatigue and technology-induced errors may not be contingent on provider aptitude. Conversely, they may be a result of human information processing limitations in stressful and chaotic environments (e.g., hospitals). Furthermore, the overexertion of a provider's cognitive abilities, by disruptive technologies or excessive alerts can create workplace environments devoid of humanity, empathy and job satisfaction. Therefore, it would be beneficial to contextualize healthcare service delivery holistically and from a journey perspective. Understanding that in addition to their illness or professional duties, patients and providers alike often experience several concurrent journeys (i.e., life events) such as: illness, grief, life stage dynamics, personal circumstance (Joseph et al., 2020). Tremendous benefit could be realized by visually identifying the pain points and intersections of the physician, patient and caregiver journey across the continuum of care (Joseph et al., 2020). A deep appreciation and understanding of individualism, human information processing capabilities could reduce provider burnout and improve patient outcomes (Joseph et al., 2020). Additionally, journey mapping activities could provide valuable insight into designing intuitive and complimentary HIT. The mapping activities and visualization outputs could illustrate healthcare complexities and delineate the intricate nuances of the varied clinical and operational workflows. Technologies designed in a patient and provider centric lens

could streamline clinical workflows, reduce healthcare costs through efficiency gains and improve patient safety.

1.3. Research objectives

This paper will explore the following research questions:

1. What is the nature of errors caused by technology (i.e., technology-induced errors) and alert fatigue in healthcare?
2. Is there a relationship between alert fatigue and technology-induced errors?
3. Do organizational strategies exist to address these problems and enhance patient safety?
4. Do technological recommendations exist to improve the current issues surrounding safety?

2. Methods

A scoping review, following the Arksey and O'Malley (2005) framework was conducted in the following databases: CINAHL®, Web of Science®, IEEE *Xplore*®, PubMed®. These databases were selected to provide a fulsome analysis of the current available indexed literature based on the search terms "Alert Fatigue" and "Technology Errors." The search included articles published in English that discussed alert fatigue and technology-induced errors in a healthcare context. The initial search yielded 81 articles, had no geographic restrictions and included all articles published prior to the year 2021. Each article was iteratively assessed (Fig. 1) by title and abstract based on the inclusion criteria. If the article met the inclusion criteria, it was read in full, the findings placed in a data extraction table (Table 1) and assessed thematically.

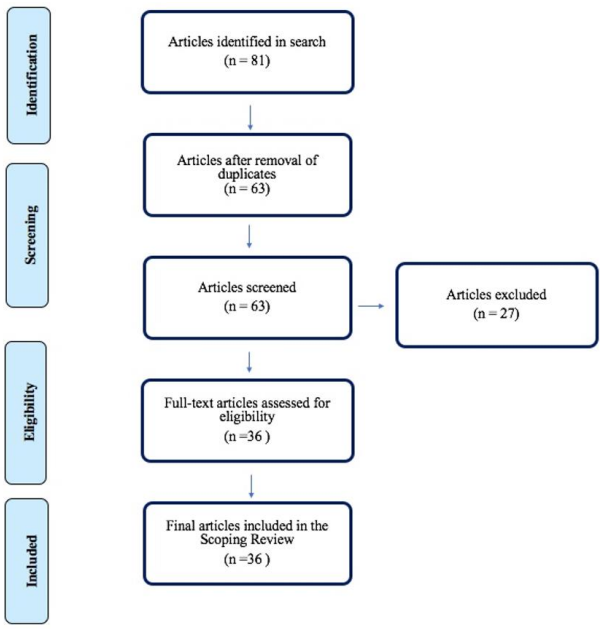

Fig. 1. PRISMA diagram. Adapted from PRISMA (2015)

3. Results

As demonstrated by Fig. 1, the article review process was iterative, and the search yielded a total of 81 articles. In the initial assessment, 18 duplicate articles were removed, and 63 articles were assessed for inclusion by title and abstract. Following this, 27 articles were removed, as they did not reference alert fatigue or technological errors in a healthcare context. Lastly, the full text review resulted in an inclusion of 36 articles with results tabulated (Table 2) and a thematic analysis conducted.

3.1. Themes from the literature

Although various themes were observed in the included literature, the four prominent themes were: alert fatigue and the appropriateness of overriding alerts, safety issues, technology as a source of errors, the importance of usability and human factors engineering.

3.2. Alert fatigue and the appropriateness of overriding alerts

Alert fatigue and the appropriateness of overriding alerts had 17 article references and was the most frequent theme of the literature sample. CDSS are often integrated with CPOE systems with the aim to improve safety by providing health professionals with point of care recommendations (e.g., alerts). However, many of the alerts are deemed clinically irrelevant contributors to alert fatigue and consequently result in system override rates of 77% to 90% (Wan et al., 2020). Furthermore, in the article by Wan et al. (2020) the authors stated that the purpose of real time alerts is to disrupt the clinical workflow, draw the providers attention away from their task and to the alert. Therefore, the intention of alert design is to prompt providers to (stop, evaluate and interpret alert notifications) make quick clinical decisions based on the information provided by the alert. However, as a result of frequent and excessive alert interruptions, medical providers are becoming less respectful and responsive to them (Wan et al., 2020). Similarly, Niazkhani et al. (2020) describe that not all CDSS are embraced by physicians and that alert fatigue is a serious concern. Furthermore, Shah et al. (2018) detail that "although smart infusion pumps are intended to prevent medication errors by alerting users about doses that exceed set thresholds, a large number of clinically insignificant alarms and alerts create the potential for alert and alarm fatigue" (Shah et al., 2018, p. 842). Moreover, Dexheimer and colleagues (2017) reported that despite 70% of hospitals in the United States of America (USA) utilizing EHRs with embedded CDSS, most alerts failed to support decision making.

Khuntia and colleagues (2015) found that because of technostress, caused by an excessive number of warnings and alerts, nurses experienced alert fatigue and increased stress while providing care. According to Herasevich et al. (2013) the complexity of intensive care unit (ICU) settings can lead to alert fatigue. Additionally, the authors described that ventilated patients attached to multiple monitoring, diagnostic and therapeutic devices can yield an activation of up to 40 alarms at any given moment (Herasevich et al., 2013). Furthermore, Herasevich et al. (2013) clarified that despite their frequency, ICU alerts rarely resulted in meaningful clinical interventions. In a related article, Lo et al. (2009) examined a non-interruptive medication alert within a longitudinal medical record. However, despite decreasing alert fatigue through non-interruptive alerts, their attempts did not change clinical behavior (Lo et al., 2009). Along these lines in an attempt to combat alert fatigue, Poly et al. (2020a) conducted the first study that utilized machine learning models to predict physician alert interactions. The

study findings revealed that the model could be utilized to identify the alert acceptance rate of individuals and reduce alert fatigue in clinical settings (Poly et al., 2020a). Zenziper Straichman et al. (2017) found that workload and scheduling greatly impacted the probability of alert override occurrence. The authors discovered that despite weekend and night shifts being associated with higher alert overrides, 88.6% of alerts were justified (Zenziper Straichman et al., 2017). Harrison et al. (2017) conducted a comparative study to establish the response rates of ICU care providers who received both EHR based alert and text message alerts. The researchers' findings indicated a favourable preference for text-based alerts for both non-urgent and urgent notifications (Harrison et al., 2017). Poly et al. (2020b) discovered that the cultural acceptance and appropriateness of alert overrides varied per clinical setting. Furthermore, they found that overrides were contingent on alert type and varied by clinical service (Poly et al., 2020b). The findings revealed that geriatric, renal and drug-drug interactions (DDIs) alerts overrides were culturally deemed inappropriate (Poly et al., 2020b). Additionally, Poly and colleagues (2020b) identified the categorical range of institutional override variance as follows: drug allergy (46%-95%), DDIs (56.3%-95.6%), medication dosage (82%-96.8%), geriatric (2.1-87.1%), renal (74.4%-97.1%). The findings of Olakotan et al. (2020) revealed that alerts should be complimentary and not disruptive and that a significant reason for alert override is the disruption to the clinical workflow.

In an article by Bryant and colleagues (2014) the authors stated, "physicians at our institution are unhappy with, and increasingly jaded by, decision support features that were intended to provide safety" (Bryant et al., 2014, p. 806). Moreover, the authors emphasized that they "are the first to report a lack of improvement in decision support acceptance (as measured by overrides) after Meaningful Use requirements took effect" (Bryant et al., 2014, p. 806). The researchers surmised that DDIs alerts may be fundamentally flawed, as the intervention did not reduce override rates of high-risk medications (Bryant et al., 2014). In fact, the study revealed that CDSS alert override rates have not statistically declined in the last 15 years (Bryant et al., 2014). The authors conclude that a more fulsome assessment of how alerts are designed is required (Bryant et al., 2014). In consideration of excessive alerts, Simpao et al. (2015) conducted a study in which visual analytic software was used to develop a dashboard to facilitate safe reductions of alerts. The researchers iteratively customized rules from a commercial EHR system and incrementally deactivated clinically irrelevant alert rules to improve medication safety while attempting to reduce alert fatigue (Simpao et al., 2015).

Riedmann et al. (2011) found that it is unclear how different severity alerts should be activated and presented to the end user in CPOE systems. Additionally, the aesthetic and mechanistic parameters of the alert notifications presented inconclusive findings (Riedmann et al., 2011). Therefore, it was unknown if specific colours, forms, screen position or if visual or auditory signals were more appealing to end users (Riedmann et al., 2011). Pohl et al. (2014) stated that depending on a patient's medical history and care plan, sometimes DDIs are unavoidable and thus alerts generated by the system are overridden. Lastly, Drew et al. (2014) disclosed that the root cause of alert fatigue is multifactorial and caused by a combination of: excessive number of physiologic monitor device alarms, a complex interplay of inappropriate user settings, patient conditions, algorithmic deficiencies. Drew and colleagues (2014) stressed the importance and value of establishing parameters for patient specific alarm notifications. The authors detailed that as a result of not customizing alerts, a patient's six day stay in the ICU resulted in an average of 211 alarms per hour (Drew et al., 2014). Furthermore, in one month alone, the number ICU alert notifications (e.g., audible, inaudible) exceeded 2,500,000 (Drew et al., 2014).

3.3. Safety issues

Although HIT is poised to increase the safety and efficiency of healthcare processes, several concerns have been identified in the literature. Eight articles specifically addressed issues of safety in healthcare settings and among healthcare stakeholders. Papadakos (2014) described that "as health professionals, we are aware of the epidemic growth of injuries and deaths related to texting and driving. It should not surprise us that this distracted behavior has affected all levels of healthcare providers and has impacted patient care" (Papadakos, 2014, p. 1306). Moreover, the author recounted that "as human communication has changed from verbal face to face communication to a world dominated by texting, tweets, e-mails, and social media, health professionals must be educated to focus on patient care. Distracted doctoring has become a major patient health concern" (Papadakos, 2014, p.1309). Keasberry et al. (2017) found that commercially and locally developed eHealth technologies appear to improve healthcare outcomes and processes across diverse settings. However, they cautioned that since eHealth technologies are evolving rapidly, evidence of their relational impact on clinical outcomes (e.g., mortality, morbid events, unplanned readmissions) remains unclear (Keasberry et al., 2017). Galt and colleagues (2019) described how HIT presents new challenges for healthcare. The authors caution, that there are inherent risks associated with HIT use, which can negatively impact patient quality and safety. (Galt et al., 2019). Along these lines in their article, Beeler and colleagues (2014) referenced a study by Han et al. (2005) which suggested a correlation between a significant increase in mortality, following the implementation of a CPOE system. The authors acknowledged that CDSS with embedded CPOE hold promise to reduce human error during healthcare delivery, but stressed the importance of monitoring medication errors and mortality rates during system implementations (Beeler et al., 2014; Han et al., 2005).

In a systematic review of prescriber education and its relationship to patient harm conducted by Bos et al. (2017), several barriers to effective prescribing were identified including: information and communication technology (ICT) shortcomings, high clinician workload, complex patient polypharmacy and medical conditions, lack of standardized processes, frequent rotations of inexperienced physicians. Comparably, Smith et al. (2013) clarified that abnormal test results do not always receive timely follow-up, even when providers are notified through EHR alerts. High workloads, alert fatigue and other attentional demands, can disrupt healthcare providers memory recall of tasks and patient care activities that may require follow up (Smith et al., 2013). The authors explained that such lapses in follow-up may lead to delays in the diagnosis and treatment of diseases such as cancer (Smith et al., 2013). Ranji and colleagues (2014) cautioned how the implementation of CPOE combined with CDSS, fundamentally changes the clinical workflow and can create new safety issues. Conversely, Ranji et al. (2014) described that despite the potential introduction of new safety issues and risks associated with using such systems, their potential ability to reduce prescribing errors remains significant. Moreover, CDSS with embedded CPOE systems can ensure that orders are legible, standardized and complete when written (Ranji et al., 2014). The findings by Otero et al. (2016) described the benefits and essential nature of HIT when cost, safety, quality and equity are considered in the broader context of healthcare. However, they also noted that unintended consequences associate with technology implementations, can affect the quality and safety of patient care (Otero et al., 2016).

3.4. Technology as a source of errors

Technology has an endless potential to improve healthcare outcomes and increase operational efficiencies in healthcare settings. However, along with the promised benefits new forms of risk and errors are often introduced (Borycki, 2013; Borycki & Kushniruk, 2017; Carvalho et al., 2009). Six articles highlighted the impacts that technology-induced errors can present in healthcare. The research published by Gold and colleagues (2015) described that when compared to traditional paper charting practices, EHRs can create errors in differing ways. Farley et al. (2013) explained that prominent areas of concern include the variance in HIT functionality and design in hospital settings. Furthermore, prescribing errors and patient harm can be caused by a combination of HIT with poor data displays and end users with alert fatigue (Farley et al., 2013). Légat et al. (2018) described that the availability of structured and accurate health information is difficult to find in EHRs. Their findings also revealed that most providers lack adequate EHR training and consequently are often unaware how to locate or document DDIs (Légat et al., 2018). Ni and colleagues (2018) highlighted that medication errors remain prominent in healthcare, despite modernization initiatives and the introduction of state-of-the-art HIT such as: EHRs, CPOE embedded systems, bar code medication administration systems, smart infusion pumps. Dilsizian and Siegel (2013) described how artificial intelligence (AI) promises improvement and opportunities for technological advancement in healthcare. However, the authors cautioned that AI initiatives can often be stifled by medicolegal and regulatory challenges (Dilsizian & Siegel, 2013). Lastly, Levick et al. (2013) evaluated the development of a CDSS alert intervention, designed to reduce the necessity of a diagnostic laboratory test. Their results indicated that the intervention reduced inappropriate orders by 21% and saved the organization $92,000 per year (Levick et al., 2013).

3.5. The importance of usability and human factors engineering

Usability engineering and human factors engineering are often viewed symbiotically in health informatics. Usability engineering can be defined as a discipline that provides structured methods for achieving usability in user interface design and during product development (Mayhew,1999). Usability from an end user context (e.g., healthcare provider) can be defined broadly as the capacity of a system to allow users to carry out their desired tasks enjoyably, safely and efficiently (Kushniruk & Patel, 2004). Whereas human factors engineering, is a discipline concerned with the design of systems, tools and machines. Human factors perspectives take into consideration human characteristics, capabilities and limitations (Gosbee, 2002). The importance of considering usability and human factors engineering in systems design was expressed by five articles in the scoping review literature sample.

Marwitz and colleagues (2019) described the need for innovation in intravenous (IV) smart pumps alerts, to decrease unnecessary alerts and improve overall usability. Their findings revealed that the majority of IV smart pump alerts were inappropriate, often caused medical errors and resulted in alert fatigue (Marwitz et al., 2019). Along these lines, King et al. (2018) found that poor human computer interaction was one of the main barriers of EHR adoption. Additionally, their research revealed that excessive interaction with EHR interfaces, can prevent physicians from interacting safely and efficiently with other technologies (King et al., 2018). Tolley and colleagues (2018) highlighted the importance of employing human factors principles in the development and design of CDSS. The authors described that alert philosophy (i.e., the reason for the alert and the severity of alert) is often not adequately communicated to end users (Tolley

et al., 2018). Furthermore, the authors noted that in addition to improving alert relevancy, other human factors should be taken into consideration with system design (Tolley et al., 2018). In keeping with these findings, Horsky et al. (2017) assessed the reasoning patterns of physicians who used HIT. Their findings revealed that the majority of physicians conceptualized risk as a complex set of interdependent and patient specific trade-offs (Horsky et al., 2017). Furthermore, the authors found that physicians "routinely left prescriptions unchanged after receiving low-severity alerts when they felt confident that patients would tolerate the drug combination and that treatment benefits outweighed the risk" (Horsky et al., 2017, p.1). Lastly, Missiakos et al. (2015) described how emerging technologies for the prevention of DDIs, were often evaluated and implemented without the input or involvement of relevant end users (e.g., healthcare providers).

3.6. Summary of the thematic analysis

The scoping review themes have been summarized (Table 2) and the thematic findings included: seventeen articles that focused on alert fatigue and the appropriateness of overriding alerts, eight articles on safety issues, six articles on technology as a source of errors, five articles that focused on the importance of usability and human factors engineering. Furthermore, Table 2 illustrates: the publication and author details, study type, object (s) of the study (i.e., the identified intervention or subject assessed in each respective article), key article highlights of potential contributing factors to alert fatigue and technology-induced errors.

Table 2
Data extraction table

Publication	Study type	Object (s) of the study	Potential contributing factors
Theme 1: Alert fatigue and the appropriateness of overriding alerts			
1. Bryant et al., 2014	Retrospective	EHR with CPOE and integrated CDSS	a) Alerts appeared too late in the clinical workflow. b) Inappropriate override classifications. c) Interruptive alert window. d) Alert notification prevents further action.
2. Dexheimer et al., 2017	Retrospective study	CDSS	a) User behavior. b) Alert overrides. c) Inappropriate alerts. d) Low specificity of alert rules.
3. Drew et al., 2014	Observational study	Physiologic monitor devices	a) Alarms not tailored to the individual patient. b) Persistent atrial fibrillation alerts. c) Limitation of device configuration. d) Adequate training not provided to clinicians.
4. Harrison et al., 2017	Simulation study	EHR based sepsis alert system (AWARE)	a) Chronic workflow interruptions. b) Human error. c) Information overload.

			d) Alerts not respected and deemed burdensome.
5. Herasevich, 2013	Descriptive	Rule – based decision support system (AWARE)	a) False alarms. b) Clinically irrelevant alarms. c) Sound pollution. d) Frustration caused by system limitations.
6. Khuntia et al., 2015	Ethnographic	Intelligent care system	a) Frequent interruption between patients. b) Technical issues. c) Inappropriate and ambiguous alert notifications. d) Alert sent to wrong provider.
7. Lo et al., 2009	Descriptive and randomized controlled trial (RCT)	Non – interruptive medication laboratory monitoring alerts	a) Lack of alert compliance. b) Deliberate choice to ignore alert. c) Passive alerts are easily ignored. d) Alert notification color scheme jarring.
8. Niazkhani et al., 2020	Descriptive	Clinical context aware CDSS	a) Workflow disruption. b) Alerts not customized to clinical specialty. c) Alerts that required too many clicks. d) Time commitment to respond to alerts.
9. Olakotan et al., 2020	Systematic review	CDSS	a) Usability problems. b) Screen displays not adequate. c) Complicated drop-down menus. d) Ambiguous code categories.
10. Pohl et al., 2014	Mixed method	EHR	a) High sensitivity setting. b) Incomplete medication lists. c) Alert severity not specified. d) Low tolerance for alert interaction.
11. Poly et al., 2020a	Model development and validation	CDSS	a) Physician culture and departmental acceptance of override appropriateness. b) Physician preferences to rely on clinical knowledge vs technology. c) Alert desensitization caused by frequent incorrect or irrelevant notifications. d) Workflow disruption.
12. Poly et al., 2020b	Systematic review	CDSS	a) Ambiguous alert content. b) Mediocre functionality. c) Erroneous alert assessment by physicians. d) Workflow disruption.

13. Riedmann et al., 2011	Literature review with qualitative interviews	CPOE systems	a) Characteristics of the patient. b) Characteristics of the organizational unit. c) Context of clinical situation. d) Perceived relevancy of the alert.
14. Shah et al., 2018	Narrative review	Smart infusion pump	a) Lengthy work arounds to avoid alerts. b) Number and frequency of clinically irrelevant alerts. c) Number and frequency of clinically relevant alerts. d) Desensitization to constant notifications.
15. Simpao et al., 2015	Cross sectional study	Electronic dashboard for EHR medication alerts	a) Highly sensitive alerts with low specificity. b) Excessive non clinically relevant DDI alert rules. c) Cluttered alert windows. d) Complicated alert messaging and resolution.
16. Zenziper Straichman et al., 2017	Retrospective and prospective study	SafeRx prescription CDSS	a) Alerts are ignored and not read by physicians. b) Desensitization to irrelevant alerts, as patients are monitored in acute care. c) DDI alerts are not accurate and are based on weight metrics, not found in the EHR. d) Frustration at alert frequency.
17. Wan et al., 2020	Scoping review	MedAlert - blockchain based alternative to CDSS	a) Workflow disruption. b) Traditional CDSS have low specificity and high volume of alerts. c) Alerts are often generated incorrectly. d) Frequent low level and high-level alerts are sent to healthcare providers.
		Theme 2: Safety issues	
18. Beeler et al., 2014	Descriptive	CDSS	a) Too many false positive alerts. b) Additional workload. c) Need for specificity of electronic notifications. d) Frustration surrounding erroneous alerts.
19. Bos et al., 2017	Systematic review	Prescriber education and medication related patient harm	a) Prescribing process limitations. b) Comorbid patients and polypharmacy. c) Workload and inadequate staffing levels.

			d) Shift and changeover personnel inconsistencies.
20. Galt et al., 2019	Descriptive	HIT	a) System information missing or incorrect. b) Drop down menu selection errors. c) Medications not found in the system. d) Human errors such as entering wrong medication or dose.
21. Keasberry et al., 2017	Narrative	Hospital-based eHealth technologies	a) Increased workload caused by technology. b) Disruption to workflow, caused by lengthy workarounds. c) The introduction of new prescribing errors, caused by lack of standardized workflow. d) Poor system design.
22. Otero et al., 2016	Non-systematic review	HIT implementation	a) Lack of technical skills to facilitate implementations. b) Lack of consideration for usability testing. c) Security concerns. d) Resource constraints.
23. Papadakos, 2014	Descriptive	Electronic distractions	a) Alarm hazards. b) Distraction from personal technology devices. c) Patient data mismatches in EHRs. d) Missing data from other HIT.
24. Ranji et al., 2014	Narrative review	CPOE with CDSS	a) Workflow changes. b) Availability and placement of workstations can impair clinician efficiency. c) System design problems. d) Data entry restrictions.
25. Smith et al., 2013	Prototype evaluation	Decision support software prototype	a) System mandated multitasking. b) Inconsistency of alert mechanism. c) Limited alert information. d) Frequent interruptions and clinical workflow disruption.
		Theme 3: Technology as a source of errors	
26. Dilsizian & Siegel, 2013	Descriptive	AI in medicine and cardiac imaging	a) Lack of access to large de-identified databases. b) Potential to disrupt clinical workflow. c) Perceived medicolegal issues. d) Regulatory and ethical challenges.

27. Farley et al., 2013	Descriptive case study	Emergency department information systems (EDIS)	a) Variance in system functionality. b) Poor data display. c) Communication failures. d) Wrong order wrong patient errors.
28. Gold et al., 2015	Descriptive	EHR	a) Communication break downs among providers. b) Inconsistent information presented in EHR. c) Clinical workflow disruption. d) Mandated reliance on technology.
29. Légat et al., 2018	Systematic review	CDSS for drug allergy	a) Stressful working conditions. b) Hospital culture and mandated reliance on technology. c) Drug coding inconsistencies. d) No documentation or reporting standards.
30. Levick et al., 2013	Descriptive evaluative intervention study	CDSS intervention in a CPOE system	a) Frequent alarms. b) Tests occurred daily and high cost. c) Intervention caused more alerts. d) Productivity loss and increased stress in workplace.
31. Ni et al., 2018	Observational study	Real time medication administration error (MAE) detection system	a) False positive alerts. b) False negative alerts. c) Documentation issues. d) Clinical errors.
Theme 4: The importance of usability and human factors engineering			
32. Horsky et al., 2017	Partial simulation and standardized scenario case study	DDI alerts	a) High proportion of alerts. b) Clinically irrelevant alerts. c) Ambiguous display of information. d) Inconsistent information.
33. King et al., 2018	Pilot simulation study	EHRs incorporated with real -time location systems (RTLS)	a) Poor human computer interactions with EHR systems. b) Number of required clicks to access patient data. c) System disrupted and complicated the clinical workflow. d) Confusion about system use.
34. Marwitz et al., 2019	Descriptive	IV smart infusion pumps with a dose – error reduction system (DERS)	a) Inconsistent institutional drug libraries. b) Inconsistent alerting practices. c) Diverse pump manufacturers and heterogenous products. d) Drug limit setting varied per institution and product.

35. Missiakos et al., 2015	Exploratory	Technologies that assist in DDI identification	a) System limitations and capabilities not adequately communicated. b) Insufficient provider training on system components. c) DDI algorithmic logic and rational for notifications not effectively provided. d) Over reliance on system for detection of DDIs.
36. Tolley et al., 2018	Extensive literature review	CDSS	a) Variability in alert type and notifications. b) Ambiguous and unknown alert severity parameters. c) Drug dosage alerts not individualized. d) Drug dosage alerts don't deliver practical alternatives.

3.7. Limitations

As this search was conducted electronically and in English, it did not include paper articles or literature published in other languages. The available literature was also constrained by the search terms, thus limiting the articles available for inclusion and analysis. Although various themes were observed in the included literature, the articles were clustered into four thematic categories. Additionally, during the interpretation phase there was potential for biases to influence the meaning of the categorical descriptors, as such cross-checks were done to bolster interpretation. An ethics consult was not required, as the study included publicly available information only.

4. Discussion

This scoping review presents an analysis of 36 articles from four established databases: CINAHL®, Web of Science®, IEEE *Xplore*®, PubMed®. Data was extracted from the articles, tabulated (Table 2) and a thematic analysis was conducted. The findings revealed that despite increasing adoption rates, collectively HIT are still considered in early stages of their system development cycles (SDLC) and additional measures are required to ensure that they continue to advance safely and effectively in industry (Kushniruk, 2002). Additionally, it was discovered that there may be a relationship between poorly designed systems and technology-induced errors. The thematic analysis presented four prominent themes: alert fatigue and the appropriateness of overriding alerts, safety issues, technology as a source of errors, the importance of usability and human factors engineering. Furthermore, the overarching theme of the four thematic categories was the importance of UX in the context of HIT design and the frequency of alert notifications.

It was revealed that the origins of technology-induced errors and alert fatigue in healthcare, could be a consequence of HIT designed and implemented without human factors and usability engineering considerations. Furthermore, many articles presented

examples where the cognitive and information processing capacity of healthcare providers was not considered in HIT design, acquisition or implementations. Such omissions are substantial, as healthcare providers are the facilitators of healthcare service delivery and the principal end users of HIT. Consequently, providers are often required to leverage various HIT during their daily activities of care, to access patient health information. These varied and siloed HIT, complicate the clinical workflow and reduce the amount of diagnostic time that providers can allocate to each patient. Sourcing health information from various locations and systems can also contribute to cognitive burden, as each respective HIT has varied display screens, alerting mechanisms and login information. Therefore, the research findings revealed that there is indeed a relationship between alert fatigue and technology-induced errors. Furthermore, accessing health data from various fragmented HIT sources can create unsustainable clinical workflows, medical errors and compromise patient care. The literature did not detail existing organizational strategies to address such problems as alert fatigue and technology-induced errors to enhance patient safety. Contrarily, the findings revealed that the combined negative consequences of medical errors caused by cognitive impairment (i.e., alert fatigue) and technology-induced errors is not yet quantifiable. In fact, it is not clear if standardized mechanisms for cross sectional evaluation exist. If they do, it is assumed that they are at the early stages of development and are not yet generalizable for use in the broader healthcare context. Therefore, it has been implied that such recorded or delineating data does not yet exist in aggregate in healthcare. Moreover, the scoping review revealed that a standardized evaluative mechanism to monitor or differentiate between error types (e.g., medical errors vs technology-induced errors) in healthcare also does not exist. Therefore, the relationship between alert fatigue and technology-induced errors is complex and not fully understood. In terms of technological recommendations to improve the current issues surrounding safety, the scoping review findings did not present recommendations, or a global cohesive strategy to mitigate such issues. Additionally, a standardized organizational approach, to addressing poorly designed technologies that may pose risks to the cognitive abilities of physicians and healthcare providers was not present in the literature.

To satisfy this gap in the literature and to further illustrate the importance and necessity of designing safe and usable HIT from an end user perspective, the authors developed the Flow of Cognitive Processing Model (Fig. 2). The model was inspired by Atkinson and Shiffrin's (1968) model of memory and Sweller's (1988) research on cognitive load theory. Fig. 2 identifies the synergies between information processing, and information saturation in the context of varied environmental stimuli exposure in healthcare settings. Although the model was intended for use in healthcare settings, the model's iterative cognitive flow cycle is applicable to any industry where technology can influence human behavior, memory, cognitive capacity in information processing. The Flow of Cognitive Processing Model illustrates the complexity of issues surrounding poorly designed HIT, that may increase cognitive burden for healthcare provider end users. The model can also be used to emphasizes how HIT can alter natural thought patterns, eye movement and human information processing capabilities. The model displays the iterative nature of information processing, as incoming stimuli is cognitively processed according to memory stage (Table 1) and human ability. Each phase of the model relates to a different aspect of memory and information processing. The model provides a systems and humanistic perspective to the correlations between clinical workflow, patient safety and illustrates how information processing is contingent on HIT design.

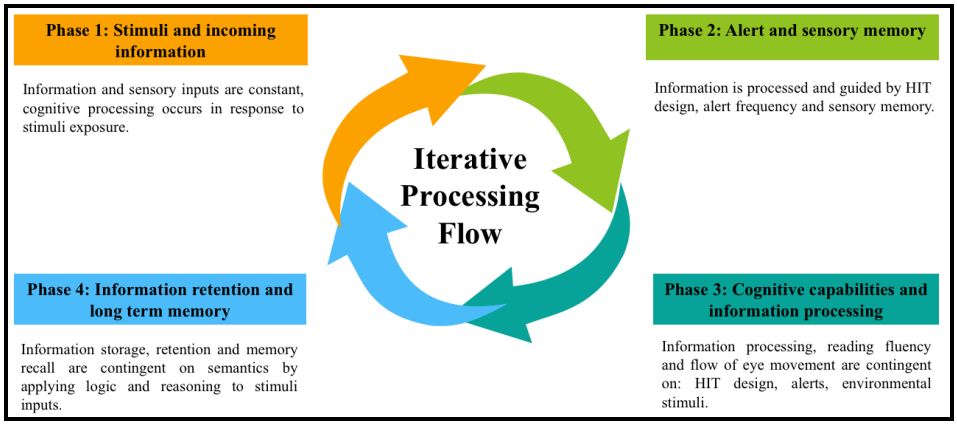

Fig. 2. Flow of Cognitive Processing Model

As detailed in Phase 1 of the Flow of Cognitive Processing Model, information processing begins with the healthcare provider receiving new information, sensory inputs, and external stimuli. Cognitive processing occurs in response to the level of stimuli that the individual is exposed to. In Phase 2 information processing is guided by HIT design, frequency of alert interruptions and sensory memory. The model demonstrates that designing HIT according to sensory memory could improve human information processing abilities. In Phase 3 of the model, information processing, reading fluency (e.g., flow and direction of eye movement) are contingent on HIT design. Therefore, the way that information is displayed on HIT screens, guides the natural path that the end users' eyes take when reading or accessing health information. Their information processing abilities are further impacted by the frequency of alert notifications embedded within HIT. These distracting alerts interrupt thought patterns, complicate clinical workflows and often prevent providers from completing intended tasks. Acute care settings are also a source of additional stimuli, as they are typically loud, chaotic environments plagued with several operational and auditory interruptions (e.g., paging or intercom systems, patient requests, conflicting priorities). Environmental overstimulation and alert fatigue may occupy the limited capacity of a provider's short-term memory and working memory (Table 1). With exhausted short-term memory and working memory reserves, it is not humanly possible for medical providers to respond to constant stimuli. Nor are they effectively able to retain or store information that could be used for providing care in their long-term memory. Therefore, Phase 3 also depicts the necessity of establishing clinical guidelines and designing HIT dashboards based on the short-term memory, working memory and long-term memory capabilities of healthcare providers. Such initiatives could reduce cognitive load and improve patient safety by reducing the risk of technology-induced errors. In Phase 4 information retention and long-term memory are activated, in that the healthcare provider's ability to recall memories moves to the forefront. The modelling is contingent on semantics, applying logic and reasoning to stimuli typically found in clinical environments. Consideration of such a model could inform the design of alerts and improve their ability to enhance safety by considering the information processing capabilities and limitations of healthcare providers.

Utilizing the Flow of Cognitive Processing Model to inform HIT design and procurement activities may result in the acquisition and implementation of patient and provider centric HIT. Fig. 2 contextualizes how interactions with technology are

complex, due to varied (e.g., provider specific) clinical workflows and siloed HIT (e.g., EHRs, clinical applications) required to support patient care. Furthermore, the model presents an iterative perspective and an insightful view into the cognitive realms of healthcare providers. Viewing the complexities of healthcare providers from a humanistic lens could aid in fostering an environment where intuitive, efficient and relevant HIT is purchased and implemented with the involvement of clinical and organizational stakeholders. Such a holistic approach to HIT acquisition and implementation could reduce alert fatigue and mitigate the introduction of technology-induced errors.

5. Conclusions

This paper has presented a variety of perspectives and research insights into the concept of alert fatigue and its relationship to technology-induced errors. The findings of the scoping review indicate that HIT pose significant promise when streamlining processes and reducing medical errors. However, there remains a critical and significant need to assess HIT from a patient safety and quality lens. Human factors perspectives and usability engineering should be considered vital aspects of the system design, testing and implementation process. Future research could include journey mapping (Joseph et al., 2020) activities with relevant healthcare stakeholders (e.g., caregivers, physicians, patients) who are experiencing alert fatigue or other challenges across the continuum of care. The insights from these mapping exercises and visualizations could address the current gaps in literature including: the benefits of journey mapping, alert fatigue, cognitive limitations of healthcare providers, importance of clinical workflow in HIT design, root cause of technology-induced errors, effective HIT implementation strategies. Illustrating the complex workflows of healthcare providers, as they circumvent constraints and barriers caused by HIT along their journey in providing care to patients is vital. Such insight could also assist decision makers in assessing hospital capacity, EHR design, patient mortality rates and other resource utilization assessments.

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