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Contents

Original Paper

Improving the Safety, Effectiveness, and Efficiency of Clinical Alarm Systems: Simulation-Based Usability
Testing of Physiologic Monitors ([e20584](#))
Azizeh Sowan, Nancy Staggars, Andrea Berndt, Tommye Austin, Charles Reed, Ashwin Malshe, Max Kilger, Elma Fonseca, Ana Vera, Qian
Chen. 2

Review

Predicted Influences of Artificial Intelligence on Nursing Education: Scoping Review ([e23933](#))
Christine Buchanan, M Howitt, Rita Wilson, Richard Booth, Tracie Risling, Megan Bamford. 12

Original Paper

Improving the Safety, Effectiveness, and Efficiency of Clinical Alarm Systems: Simulation-Based Usability Testing of Physiologic Monitors

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Abstract

Background: Clinical alarm system safety is a national patient safety goal in the United States. Physiologic monitors are associated with the highest number of device alarms and alarm-related deaths. However, research involving nurses' use of physiologic monitors is rare. Hence, the identification of critical usability issues for monitors, especially those related to patient safety, is a nursing imperative.

Objective: This study examined nurses' usability of physiologic monitors in intensive care units with respect to the effectiveness and efficiency of monitor use.

Methods: In total, 30 nurses from 4 adult intensive care units completed 40 tasks in a simulation environment. The tasks were common monitoring tasks that were crucial for appropriate monitoring and safe alarm management across four categories of competencies: admitting, transferring, and discharging patients using the monitors (7 tasks); managing measurements and monitor settings (23 tasks); performing electrocardiogram (ECG) analysis (7 tasks); and troubleshooting alarm conditions (3 tasks). The nurse-monitor interaction was video-recorded. The principal investigator and two expert intensive care units nurse educators identified, classified, and validated task success (effectiveness) and the time of task completion (efficiency).

Results: Among the 40 tasks, only 2 (5%) were successfully completed by all the nurses. At least 1-27 (3%-90%) nurses abandoned or did not correctly perform 38 tasks. The task with the shortest completion time was "take monitor out of standby" (mean 0:02, SD 0:01 min:s), whereas the task "record a 25 mm/s ECG strip of any of the ECG leads" had the longest completion time (mean 1:14, SD 0:32 min:s). The total time to complete 37 navigation-related tasks ranged from a minimum of 3 min 57 s to a maximum of 32 min 42 s. Regression analysis showed that it took 6 s per click or step to successfully complete a task. To understand the nurses' thought processes during monitor navigation, the authors analyzed the paths of the 2 tasks with the lowest successful completion rates, where only 13% (4/30) of the nurses correctly completed these 2 tasks. Although 30% (9/30) of the nurses accessed the correct screen first for task 1 and task 2, they could not find their way easily from there to successfully complete the 2 tasks.

Conclusions: Usability testing of physiologic monitors revealed major ineffectiveness and inefficiencies in the current nurse-monitor interactions. The results indicate the potential for safety and productivity issues in completing routine tasks. Training on monitor use should include critical monitoring functions that are necessary for safe, effective, efficient, and appropriate

monitoring to include knowledge of the shortest navigation path. It is imperative that vendors' future monitor designs mimic clinicians' thought processes for successful, safe, and efficient monitor navigation.

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KEYWORDS

usability testing; clinical alarms; fatigue; critical care; patient safety; nursing

Introduction

Background

Closely observing the physiologic condition of critically ill patients is an essential and complex task that involves the use of sophisticated, computerized, and alarm-equipped physiologic monitors [1]. Research shows that an excessive number of false alarms (86%-99.5%) from physiologic monitors leads to a phenomenon called alarm fatigue [2-8], which further results in nurses having to respond to an average of 150-400 alarms per patient per day in intensive care units (ICUs) [9] and, more startlingly, ignoring alarms or inappropriately turning off alarms [10]. The Joint Commission and the Food and Drug Administration (FDA) attributed fatal alarm-related incidents to alarm fatigue [11,12]. As a result, The Joint Commission's 2014 National Patient Safety Goal NPSG.06.01.01 mandated improving the safety of clinical alarm systems [13]. This study examined critical patient safety and usability problems related to physiologic monitors used by nurses in 4 adult ICUs. This study describes physiologic monitor use and alarm management effectiveness and efficiency—two goals of usability [14-16]. Self-perceived competence and nurse satisfaction with the use of monitors—a third goal of usability—was described elsewhere [17].

Gap in Knowledge

Physiologic monitors, mostly heavily used by nurses, were associated with the highest number of alarms and alarm-related deaths in the FDA's Manufacturer and User Facility Device Experience database and in previous research studies [12]. However, research involving nurses' use of physiologic monitors is rare. The identification of critical usability issues for monitors, especially those related to patient safety, is a nursing imperative. The poor usability of physiologic monitors was one of the main themes identified by nurses in a recent study where changes in default alarm settings and standardized in-service education on monitor use were insufficient to improve the safety of the alarm system [10]. Nurses stated that the complexity of navigating monitors to manage parameters and alarm settings negatively affects the appropriate management of clinical alarms, threatens the timely recognition and response to lethal alarms, and induces high levels of frustration and unsafe workarounds among nurses [10]. Usability is a national priority for health care software. The 2012 Institute of Medicine report "Health Information Technology and Patient Safety: Building Safer Systems for Better Care" identified software usability as a critical attribute for patient safety [18]. However, little information is available about medical device usability, especially for nurses and specifically for clinical alarms management.

Study Aims

The specific aims of this simulation-based usability study are directed toward the effectiveness and efficiency of bedside physiologic monitors and alarm management. The aims are consistent with usability attributes identified by the Institute of Medicine and human factor and usability engineering frameworks [14,15,18]. During observations of ICU nurses' interactions with bedside physiologic monitors in a simulated environment, the study aims to: (1) examine successful task completion in the navigation of monitors (effectiveness), (2) examine the nurses' thought processes during monitor navigation (effectiveness), (3) calculate the time required by nurses to navigate the monitors to perform different tasks (efficiency), and (4) calculate the number of clicks or steps it requires nurses to complete a monitor navigation task (efficiency).

Methods

Setting, Design, and Sample

The target units of this usability study were adult ICUs at a 705-bed university teaching hospital in the southwestern part of the United States. The ICUs were transplant and cardiac (37 nurses, 26 beds), surgical and trauma (55 nurses, 30 beds), neuro (28 nurses, 26 beds), and medical (53 nurses, 26 beds) units. The 4 ICUs have an annual admission rate of 5000 patients. After the approval by the institutional review board and following the recommendations by Faulkner for sample size in usability research [19], this interventional study used a convenience sample of 30 nurses from all the 4 ICUs. The study was conducted in a simulated environment using one of the ICU beds, a case scenario, a Philips IntelliVue MX800 bedside monitor, and a Philips IntelliVue Information Center iX central station monitor. The monitors are currently used in all the ICUs and have complex information systems that are capable of capturing, displaying, and storing waveforms; parameters and alarms; and include many menus, buttons, and icons for user navigation.

Description of Tasks

The usability testing methods described here are congruent with the widely accepted usability techniques related to user tasks and outcome measures [14-16,18]. The principal investigator of the study and 3 expert ICU nurse educators created a short case scenario followed by 12 updates and/or changes in the patient's medical condition and asked nurses to complete 40 tasks. Each update and/or a change in the patient's medical condition was followed by a set of specific tasks. The case scenario, updates and/or changes in the patient's medical condition, and the associated tasks were evaluated for face validity by 3 expert ICU nurses who assessed the appropriateness and complexity of tasks using a checklist and

were piloted in the simulation environment for content, timing, and any methodological issues. Tasks were typical across all the ICUs and represent common monitoring tasks that are critical for appropriate monitoring and safe alarm management. Sowan and colleagues identified these tasks as a basic set of competencies for appropriate and safe monitoring operations [17]. The tasks targeted the following competencies and navigation actions [17]:

1. Admit, transport, and discharge patients using the monitors. Patient information needs to be correctly entered into the monitor for it to select the appropriate algorithm and calculate hemodynamic, oxygenation, and ventilation parameters for safe alarm limits. Nurses also need to know how to connect the monitor's cables for multiparameter monitoring when a patient is admitted. The case scenario included 7 tasks in this category.
2. Manage measurements and monitor's settings. After setting up the monitor and admitting a patient to the monitor, most of the nurses' time is usually directed toward managing measurements and monitor's settings. Examples include selecting the appropriate parameters for the patient condition, customizing measurement, and setting alarm limits to patient specific (ie, deactivating unnecessary parameters, setting the appropriate paced mode), adjusting the alarm volume and screen brightness, and adjusting the speed and size of the waves. The case scenario included 23 tasks.
3. Perform electrocardiogram (ECG) analysis. Performing a 12-lead ECG includes entering an order into the monitor, storing and sending the 12-lead ECG to the central monitor, and exporting the 12-lead ECG to the cardiology management system. The case scenario included 7 tasks related to the competency of analyzing the ECG.
4. Troubleshoot alarm conditions. Nurses are expected to troubleshoot common technical alarms (such as a lead-off alarm) and to follow the unit policy when they are troubleshooting alarms. The case scenario included 3 of these tasks.

Study Procedure

Participation sessions were scheduled individually and video-recorded. Two expert nurse educators served as the moderators for the testing sessions and prepared the monitors based on the case scenario and tasks. Upon arrival, each participating nurse received a testing packet with a unique ID. The packet included directions for participation, a demographic form, the case scenario, and the tasks nurses need to execute using the monitors. Updates and changes in the patient medical condition in the testing packets were presented in a random order with the associated tasks on a separate page. Nurses were directed to complete the tasks in the order received and to think aloud for 3 tasks where no monitor-nurse interaction was possible (mentioned below). Nurses were asked to complete all the tasks, including those they did not know how to perform and indicate whether and when they would like to give up trying to perform a task. The moderator guided the nurse through the testing process, reminded the participant to think aloud when necessary, video-recorded the testing session, and printed the reports of the monitor settings before and after participation.

Because, in real life, nurses use the bedside monitors to set parameters and manage alarms, in this simulation study, efficiency and effectiveness of task completion were based on navigating the bedside monitor. The central station monitor was used to print reports of the settings of the bedside monitor pre- and postparticipation to measure the effectiveness of task completion.

Outcome Measurements

The main outcome measures were effectiveness and efficiency in monitor use. Effectiveness was related to the success of completing the tasks in the case scenario and understanding the thought processes for task completion. Efficiency was concerned with the time of task completion and the number of clicks/steps taken for task completion.

Effectiveness

The principal investigator and 2 expert ICU nurse educators viewed all the videos and identified, classified, and validated successful task completion. The reports of parameters and alarm limits that were printed by the moderator from the central station monitor before and after each testing session were also used to validate the changes made by the participating nurse while judging the success of task completion. Furthermore, the nurse's inability to complete a task was recorded as an unsuccessful completion of a task.

Efficiency

Efficiency was measured by the time of task completion (aim 2) and the number of clicks/steps taken for task completion (aim 3). Different screens and paths of navigation within the monitor are available to allow nurses to interact with the monitor. Nurses are expected to always select a short navigation path for task completion to enhance productivity and response to alarms. Understanding the navigation path of software is critical for identifying factors that may contribute to errors, efficiency, and catastrophic usability problems (eg, lack of responsiveness of the monitor to the change intended by nurses). The principal investigator and 2 expert ICU nurse educators viewed all the videos for the recorded start and end times for each task and determined efficient pathways for task completion. The time for each task started from the time the nurse started interacting with the monitor. In total, 3 of the 40 tasks did not require monitor navigation; therefore, efficiency was limited to 37 navigation-related tasks.

Data Analysis

Descriptive statistics were used to describe the sample characteristics and main study outcomes. The success of task completion and time were presented for each task. Simple regression analysis was used to measure the association between the number of clicks/steps taken per task and time in seconds for task completion.

Results

Nurse Characteristics

A total of 30 nurses participated in the simulation study. The majority of the nurses were from neuro ICU (14/30, 47%) and

surgical trauma ICU (11/30, 37%), females (25/30, 83%), full-time employees (18/30, 60%), with less than 3 years of experience in their ICU (19/30, 63%), had 3 or more years working as a nurse (17/30, 57%), and had not received training on the monitors within the last 2 months (25/30, 83%).

Effectiveness of Task Completion

Among the 40 tasks, only 2 (5%) were completed correctly by all the 30 nurses (ie, “take the monitor out of standby” and “verify noninvasive blood pressure [NBP] is set to every 15 min”). At least one (1/30, 3%) nurse abandoned or did not successfully perform 38 tasks. In total, 50% (15/30) to 90% (27/30) of the nurses could not successfully complete 8 tasks. The tasks with the lowest successful completion rates were “explain how to change resuscitation status in the monitor” (completion rate was 3/30, 10% nurses); “adjust screen brightness to 7” (4/30, 13% nurses); “record a 25 mm/s ECG strip of any of the ECG leads” (4/30, 13% nurses); “troubleshoot the source of alarm by making sure X2 (transport monitor) is synched correctly to bedside monitor” (6/30, 20%); “verify the source of alarm is from MAP (mean arterial pressure) and systolic and change source if needed” (9/30, 30%); “disconnect the X2 and place bedside monitor on standby” (12/30, 40%); “troubleshoot false ECG alarms on the monitor” (15/30, 50%); and “change NBP MAP lower limit to 65” (15/30, 50%).

To understand the nurses’ thought processes during monitor navigation, the authors analyzed the paths of the 2 tasks with the lowest successful completion rates, where only 13% (4/30) of the nurses completed correctly: “record a 25 mm/s ECG strip of any of the ECG leads” and “adjust screen brightness to 7.” [Multimedia Appendix 1](#) shows 2 correct paths followed by nurses who took 6 and 7 steps to “record a 25 mm/s ECG strip of any of the ECG leads.” Based on the correct paths, the key steps for task completion were *taskbar* and *recording*. [Multimedia Appendix 1](#) also shows the analysis of the first 3

steps performed by the nurses who unsuccessfully completed the task. For example, 27% (8/30) nurses started the task by accessing the *xheart rate (HR) waveform* screen, 20% (6/30) started by *taskbar*, and 10% (3/30) started by *HR numeric*. The most common second step (15/30, 50% of the nurses) was scrolling back and forth for 1, 2, 3, or 4 times. It appears that these nurses were trying to find the best screen to click next to record a 25 mm/s ECG strip. Some nurses also accessed *12-lead*, *capture 12-lead*, *capture ECG*, and *setup ECG* as a second step (5/30, 17%). *Capture 12-lead* and *setup ECG* were also clicked by 33% (10/30) nurses as a third step for task completion.

Similarly, for “adjust screen brightness,” the key screen for a successful path was *user interface*, which can be accessed after the *main setup screen*. Although 30% (9/30) of the nurses who unsuccessfully completed this task accessed the *main setup* first, they unsuccessfully scrolled back and forth or accessed *equipment* as their second step to change the screen brightness. The *main setup* was accessed in the first (9/30, 30%), second (2/30, 6%), and third (2/30, 6%) steps by nurses, but it appears that nurses did not know what to click next to adjust brightness.

Efficiency in Task Completion

Efficiency analysis focused on the time to *successfully* complete the task because among nurses who could not successfully perform the task, some nurses gave up quickly, whereas others spent more time trying to complete a task. [Tables 1-4](#) present the mean time and range (in min:s) for successful task completion. The tables include the time to complete 37 (vs 40) tasks. Time was not recorded for the following 3 tasks because they were explained by nurses during the simulation and they required no to minimal monitor-nurse interaction: (1) “what would you do if you had INOP (inoperative or technical) alarm and didn’t know how to troubleshoot it,” (2) “explain how to change the resuscitation status in the monitor,” and (3) “explain how to discharge a patient from the monitor.”

Table 1. Mean time for task completion (min:s) for admission, discharge, and transfer-related tasks (N=30 nurses).

Task	Task completion time		Successfully completed tasks, n (%)
	Mean (SD)	Range	
Take the monitor out of standby	0:02 (0:01)	0:01-0:08	30 (100)
Disconnect the X2 ^a and place bedside monitor on standby	0:08 (0:08)	0:02-0:59	12 (40)
Select the correct patient profile	0:11 (0:06)	0:02-0:32	22 (73)
Reconnect X2 and readmit the patient to the bedside monitor	0:20 (0:16)	0:05-1:15	26 (87)
Set up the cables for each A-line ^b and CVP ^c	0:27 (0:17)	0:06-1:28	26 (87)
Admit the patient into the monitor	1:11 (0:29)	0:31-2:02	28 (94)

^aX2: name of the transport monitor.

^bA-line: arterial line.

^cCVP: central venous pressure.

Table 2. Mean time for task completion (min:s) for managing measurements and monitor settings-related tasks (N=30 nurses).

Task	Task completion time		Successfully completed tasks, n (%)
	Mean (SD)	Range	
Adjust alarm volume to be quieter	0:03 (0:02)	0:02-0:09	23 (77)
Print parameters' limits for all active alarms	0:04 (0:03)	0:01-0:15	27 (9)
Verify that NBP ^a is set to q15 min	0:05 (0:03)	0:02-0:16	30 (100)
Pause ABP ^b /ART ^c alarm while A-line ^d is being inserted	0:06 (0:06)	0:01-0:30	24 (80)
Identify on the screen for how long the alarm will be paused	0:07 (0:06)	0:02-0:28	26 (87)
Deactivate ART alarm	0:09 (0:05)	0:04-0:30	28 (93)
Verify vitals are displayed: NBP, Temp ^e , RR ^f , SpO ₂ ^g	0:09 (0:10)	0:02-0:53	26 (87)
Adjust RR waveform size up	0:10 (0:06)	0:05-0:33	24 (80)
Display the missing vitals	0:10 (0:09)	0:02-0:32	26 (87)
Turn on QRS ^h volume on SpO ₂ and turn off the volume	0:13 (0:06)	0:06-0:33	26 (87)
View upper/lower limits of active parameters	0:13 (0:07)	0:03-0:36	27 (90)
Adjust alarm volume to be louder	0:13 (0:11)	0:02-0:42	25 (83)
Change wave speed on SpO ₂ to be faster	0:14 (0:09)	0:02-0:37	19 (63)
Change paced mode to off	0:14 (0:20)	0:01-1:27	19 (63)
Change upper and lower values of heart rhythms	0:15 (0:06)	0:06-0:40	29 (97)
Change upper or lower blood pressure limits to patient specific	0:23 (0:09)	0:11-0:52	27 (90)
Verify source of alarm is from MAP ⁱ and systolic	0:26 (0:26)	0:07-1:25	9 (30)
Change NBP MAP lower limit to 65	0:30 (0:28)	0:03-1:26	15 (50)
Adjust screen's brightness up to 7	0:37 (0:12)	0:28-0:54	4 (13)
On X2 ^j , change SpO ₂ to Res ^k	0:38 (0:19)	0:13-1:27	17 (57)
Verify waveforms for A-line/CVP ^l parameters are displayed	0:38 (0:55)	0:04-4:03	22 (74)
Turn A-fib ^m and irregular HR ⁿ to off	0:42 (0:18)	0:20-1:26	16 (54)

^aNBP: noninvasive blood pressure.

^bABP: arterial blood pressure.

^cART: alternative arterial.

^dA-line: arterial line.

^eTemp: temperature.

^fRR: respiratory rate.

^gSpO₂: peripheral capillary oxygen saturation.

^hQRS: a name of a wave in the electrocardiogram.

ⁱMAP: mean arterial pressure.

^jX2: name of the transport monitor.

^kRes: respiration.

^lCVP: central venous pressure.

^mA-fib: atrial fibrillation.

ⁿHR: heart rate.

Table 3. Mean time for task completion (min:s) for performing electrocardiogram analysis-related tasks (N=30 nurses).

Task	Task completion time		Successfully completed tasks, n (%)
	Mean (SD)	Range	
Print ECG ^a report	0:03 (0:02)	0:01-0:15	27 (90)
Export ECG	0:04 (0:03)	0:01-0:21	27 (90)
Switch the primary lead to lead III	0:08 (0:04)	0:04-0:27	29 (97)
Perform 12-lead ECG, enter the order #	0:08 (0:08)	0:11-1:25	18 (60)
Show ECG analysis	0:10 (0:06)	0:01-0:09	20 (67)
Store and send ECG analysis	0:31 (0:17)	0:01-0:12	28 (93)
Record a 25 mm/s ECG strip of any of the ECG leads	1:14 (0:32)	0:27-1:39	4 (13)

^aECG: electrocardiogram.

Table 4. Mean time for task completion (min:s) for performing troubleshooting alarms-related tasks (N=30 nurses).

Task	Task completion time		Successfully completed tasks, n (%)
	Mean (SD)	Range	
Troubleshoot false ECG ^a alarms on the monitor	0:21 (0:16)	0:03-0:53	15 (50)
Troubleshoot source of alarm by making sure X2 ^b is synched to bedside	0:29 (0:14)	0:14-0:54	6 (20)

^aECG: electrocardiogram.

^bX2: name of the transport monitor.

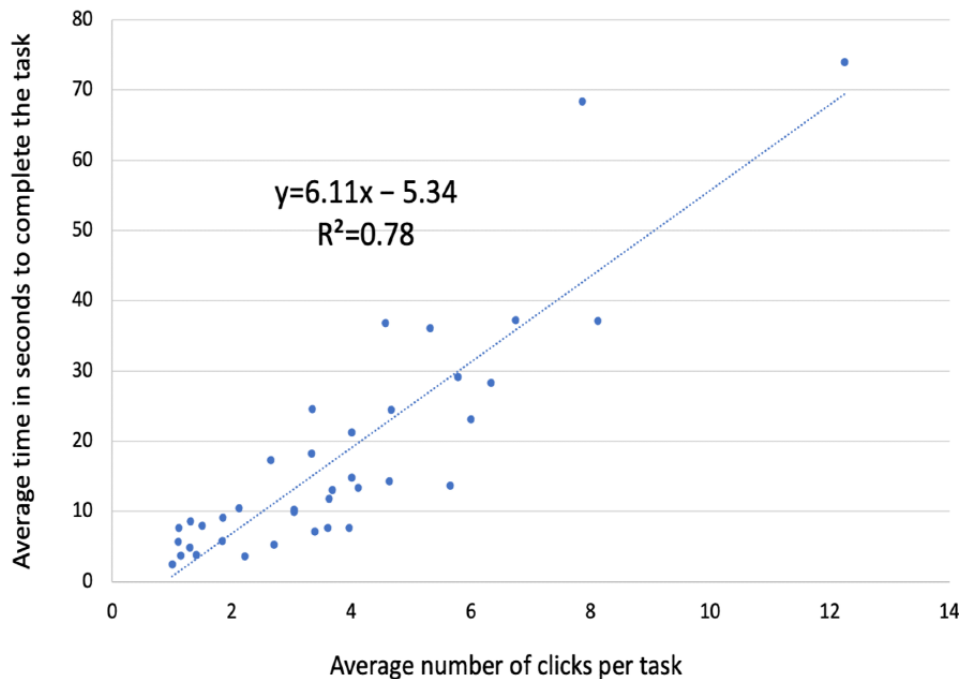
The task “Take monitor out of standby” had the shortest completion time (Table 1, mean 0:02, SD 0:01 min:s), whereas the task “record a 25 mm/s ECG strip of any of the ECG leads” had the longest completion time (Table 3, mean 1:14, SD 0:32 min:s). The task completion time range in Tables 1-4 provides valuable information about the variation in time it took nurses to successfully complete the tasks. For example, although the task “verify waveforms for A-line (arterial line) or CVP (central venous pressure) parameters are displayed” took nurses an average of 38 s to successfully complete it (mean 0:38, SD 0:55 min:s), some nurses spent only 4 s to complete this task, whereas other nurses spent as long as 4 min to complete it (Table 2). Across nurses, the minimum total time for task completion for

all 37 tasks was 237 s (3 min 57 s), whereas the maximum was 1962 s (32 min 42 s).

A linear regression analysis (Figure 1) of mean successfully completed tasks (N=37) revealed that it took nurses 6.11 s per additional click (or a step) on the monitor to perform a task during monitor navigation ($y=6.11-5.34$, $R^2=0.78$, $P=.001$).

Among task completers, some nurses completed a task in the first attempt, whereas other nurses took more than one attempt. Nurses who completed the tasks in the first attempt took an average of 3.5 clicks (or steps) and 16.5 s per task as compared with 8 clicks and 35 s per task for those who completed the tasks in more than one attempt.

Figure 1. Regression analysis of mean number of clicks taken per task and average time in seconds for a successful task completion (N=37 tasks).



Discussion

Principal Findings

The past few years have witnessed a growing number of quality improvement and interventional research studies directed toward reducing alarm fatigue and improving alarm system safety [10,20,21]. Efforts focused on pulse oximetry and physiologic monitors, including tight versus loose peripheral capillary oxygen saturation alarm strategy [20], patient-customized monitoring bundles and thresholds [10,21-23], nurse education [10], and utilization of patient profiles and updated bedside visual reminders [23]. Although these efforts led to a significant reduction in the number of nuisance alarms, the reduction was insufficient to improve nurses' attitudes toward alarms or their perceptions of alarm fatigue in ICUs [10]. The complexity of modern alarm devices requires usability testing for a safe and efficient operation of medical devices [24]. To our knowledge, this is the first study to examine the usability of physiologic monitors, the number one device associated with sentinel events in the FDA database, and the one with the highest number of nonactionable alarms [11,12].

This study examined nurses' effectiveness and efficiency in completing 40 common tasks as nurses interacted with bedside physiologic monitors. The results indicate the potential for continued safety issues in completing the routine monitoring tasks. Not a single nurse performed all the tasks correctly, and some performed more than one incorrectly. Surprisingly and perhaps even startlingly, many of these tasks represent routine everyday-monitoring tasks such as, "verify certain vitals are displayed on the monitor," "view upper and lower limits of all parameters," "display missing vitals in the monitor," "print alarm parameters' limits," "verify that NBP is set to q 15 min," and "set up the cables for each A-line and CVP." Other tasks were critical to customizing parameters to be patient specific, individualizing the monitoring process, eliminating over-and

undermonitoring, decreasing the number of unnecessary alarms, and thereby improving nurse safety and productivity in monitoring and decreasing alarm fatigue. Examples of these tasks are "change paced mode to off," "switch the primary lead to lead III," "change upper and lower heart rhythms," "select the correct patient profile," "change upper and lower blood pressure limits to patient specific," "turn atrial fibrillation and Irregular HR to off," "pause the ABP (arterial blood pressure)/ART (alternative arterial) alarm while the line is being inserted," "change NBP MAP lower limit to 65 on the monitor," and "deactivate ART parameter."

Some nurses were also unable to "admit the patient into the monitor," "reconnect X2 and readmit patient to bedside monitor," "take monitor out of standby," and to "explain how to discharge a patient from the monitor." However, it is important to note that these skills are context-specific. For example, when this study was conducted, part of a nurse's job was to admit the patient into the monitor. This process was recently streamlined, and patients are now admitted into the monitor via our admission, discharge, and transfer department. Similarly, all monitors are set to brightness level 5. Tasks such as "adjust brightness of screen up to 7" might not be as frequently used as other tasks; however, this is an important design feature for screen visibility. In addition, the monitor allows nurses to adjust the alarm volume, which is a critical function to provide a quieter care environment, specifically during the night shift, and improve patients' Hospital Consumer Assessment of Healthcare Providers and Systems scores. However, 10 (out of 30) of our nurses were unable to perform this task.

Regarding efficiency, there was a 30-min difference between the shortest and longest times to correctly perform the 37 navigation-related tasks. The monitor allows nurses to perform tasks using different navigation paths. Some paths are shorter than others, but both types of paths are rated as correct in a

successful task completion. For example, a nurse admitted a patient to the monitor using the following 5-click (or steps) navigation path and completed the task in 31 s: “(1) patient demographics, (2) admit patient, (3) MRN (medical record number), (4) VIN # (visit identification number), and (5) confirm,” whereas another nurse took 2 min 2 s to complete the same task following a longer 11-click navigation path: “(1) main setup, (2) taskbar, (3) arrow X1, (4) patient demographics, (5) MRN #, (6) VIN #, (7) confirm, (8) last name, (9) first name, (10) confirm, and finally (11) main screen.” Regression analysis revealed that nurses took 6.11 s per additional click (or step) on the monitor to successfully perform a task during monitor navigation. Our results also suggest that training nurses on the shortest navigation paths could save up to 30 min per nurse to complete the 37 routine monitor navigation tasks examined here.

The results also showed that some nurses followed a definitive short path in correctly performing a task, whereas other nurses successfully completed a task using multiple attempts, may be as a “trial and error.” For example, one nurse followed the following path to “change paced mode to off” and completed the task in 2 s and 3 clicks: “(1) patient demographics, (2) paced mode, and (3) off,” whereas another nurse used trial and error to complete the same task as evidenced by entering and exiting multiple screens searching for the parameter to be changed and managed to complete the task in 27 s and 10 clicks: “(1) HR waveform, (2) *exit*, (3) main setup, (4) equipment, (5) *exit*, (6) main setup, (7) *exit*, (8) measurement, (9) paced mode, and (10) off.” Nurses who successfully completed the tasks but performed more than one attempt used on an average 5 extra clicks per task and 18 extra s per task compared with those who completed the tasks at the first attempt. These results reflect a lack of familiarity with the task and the most efficient navigation path in the monitor to complete tasks. This provides further evidence for the need for detailed training on monitor use.

Nurse-monitor navigation is a complex cognitive process that requires adherence to policies and procedures, a usable monitor design, sufficient training on monitor functions, and the use of clinical reasoning for appropriate monitoring to eliminate over- or undermonitoring. Understanding this cognitive process is critical for safe and appropriate monitoring. For example, all the nurses who were unable to successfully complete “pause the ABP/ART alarm while the line is being inserted” task navigated to *setup ABP* or *ABP numeric* to complete the task. It appears that nurses were expecting to complete the task from the accessed screens (*setup ABP* or *ABP numeric*). This result demonstrates the importance of designing a monitor’s functions in a way that mimics clinicians’ thought processes for a successful navigation. Analyzing the paths of the two tasks with the lowest successful completion rates supported these results.

For example, although almost half of the nurses accessed the *main setup* during monitor navigation to adjust the screen brightness, none of these nurses accessed *user interface* as a subsequent step. Supporting the fact that nurses did not think that brightness can be found under *user interface* screen. Similarly, to record an ECG strip, many of the nurses navigated *12-lead*, *capture 12-lead*, *capture ECG*, or *setup ECG* screens instead of *taskbar* or *HR numeric* screens. In fact, it makes sense to complete such a task under the screens visited by nurses.

Limitations

The study results should be interpreted considering the following limitations. First, the study included a sample size appropriate for usability studies. Nevertheless, the sample size was only 17.3% (30/173) of the 173 ICU nurses in all the 4 adult ICUs. Including a stratified sample representing all ICUs could improve the generalizability of the study. A criticism might be that the convenience sample resulted in nurses with slower efficiency time to participate in the study. However, we contend that nurses who were not confident in using monitors would not have self-selected to be in this study. A stratified sample might cause even more variable efficiency and effectiveness results. Second, monitoring policies are context-sensitive. For example, in some hospitals, customizing parameters and alarm limits to patient-specific ones is the job of a physician and not a bedside nurse. Adherence to monitoring policy within a specific context is important for a valid usability test; however, it may limit the generalizability of the study. Third, vendors may have their own terminologies built into their particular monitors. For example, the term INOP alarm is specific to Philips monitors and not applicable to the General Electric monitors. Replicating this study in other hospitals would require the use of appropriate terminologies that are applicable to the medical device under study. Fourth, this study examined 40 common nurse-monitor navigation tasks. The rapid advancements in technology may eliminate some of these tasks or add to the list of tasks that nurses can perform using the monitors in the future. Future researchers will want to reassess the task lists.

Conclusions

Usability testing of physiologic monitors in this setting revealed major ineffectiveness and inefficiencies in nurse-monitor interactions. The results have implications for both safety and productivity. Training on monitor use should include critical monitoring tasks and functions that are necessary for safe and appropriate monitoring as well as the shortest path to navigate the monitor to increase nurse productivity and response to alarms. An imperative is for vendors to design the monitoring functions to mimic clinicians’ thought processes for a successful, safe, and efficient monitor navigation.

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Conflicts of Interest

None declared.

Multimedia Appendix 1

Analysis of nurses' thought processes during task completion.

[[DOCX File, 15 KB - nursing_v4i1e20584_app1.docx](#)]

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Abbreviations

ABP: arterial blood pressure
A-line: arterial line
ART: alternative arterial
CVP: central venous pressure
ECG: electrocardiogram
FDA: Food and Drug Administration
HR: heart rate
ICU: intensive care unit
INOP: inoperative or technical
MAP: mean arterial pressure
MRN: medical record number
NBP: noninvasive blood pressure
VIN: visit identification number
X2: name of the transport monitor

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Review

Predicted Influences of Artificial Intelligence on Nursing Education: Scoping Review

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Abstract

Background: It is predicted that artificial intelligence (AI) will transform nursing across all domains of nursing practice, including administration, clinical care, education, policy, and research. Increasingly, researchers are exploring the potential influences of AI health technologies (AIHTs) on nursing in general and on nursing education more specifically. However, little emphasis has been placed on synthesizing this body of literature.

Objective: A scoping review was conducted to summarize the current and predicted influences of AIHTs on nursing education over the next 10 years and beyond.

Methods: This scoping review followed a previously published protocol from April 2020. Using an established scoping review methodology, the databases of MEDLINE, Cumulative Index to Nursing and Allied Health Literature, Embase, PsycINFO, Cochrane Database of Systematic Reviews, Cochrane Central, Education Resources Information Centre, Scopus, Web of Science, and Proquest were searched. In addition to the use of these electronic databases, a targeted website search was performed to access relevant grey literature. Abstracts and full-text studies were independently screened by two reviewers using prespecified inclusion and exclusion criteria. Included literature focused on nursing education and digital health technologies that incorporate AI. Data were charted using a structured form and narratively summarized into categories.

Results: A total of 27 articles were identified (20 expository papers, six studies with quantitative or prototyping methods, and one qualitative study). The population included nurses, nurse educators, and nursing students at the entry-to-practice, undergraduate, graduate, and doctoral levels. A variety of AIHTs were discussed, including virtual avatar apps, smart homes, predictive analytics, virtual or augmented reality, and robots. The two key categories derived from the literature were (1) influences of AI on nursing education in academic institutions and (2) influences of AI on nursing education in clinical practice.

Conclusions: Curricular reform is urgently needed within nursing education programs in academic institutions and clinical practice settings to prepare nurses and nursing students to practice safely and efficiently in the age of AI. Additionally, nurse educators need to adopt new and evolving pedagogies that incorporate AI to better support students at all levels of education. Finally, nursing students and practicing nurses must be equipped with the requisite knowledge and skills to effectively assess AIHTs and safely integrate those deemed appropriate to support person-centered compassionate nursing care in practice settings.

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KEYWORDS

nursing; artificial intelligence; education; review

Introduction

Artificial Intelligence

Artificial intelligence (AI) has been defined as technology that enables a computer system or computer-controlled robot to “learn, reason, perceive, infer, communicate, and make decisions similar to or better than humans” [1]. AI is interwoven in our everyday lives through our use of technologies such as cellular phones, smart televisions, and wearable fitness devices. New AI technologies are rapidly emerging, and within health systems, the use of AI health technologies (AIHTs) has become increasingly popular owing to their capacity for sorting and analyzing large amounts of research evidence, as well as clinical and patient data to identify patterns that enhance knowledge generation and decision making [2]. Based on these capabilities, AIHTs are predicted to transform various aspects of health systems in the coming decade.

In Canada, nurses represent the largest group of regulated health professionals, accounting for approximately 50% of the health workforce [3]. As AIHTs become more pervasive in the Canadian health system, it is predicted that nurses will function in greatly different roles and care delivery models [4]. These new roles and models will necessitate changes to nurses’ core competencies and educational requirements.

In the last 5 years, multiple expository papers and research studies have explored the current and predicted influences of AIHTs on nurse educators, nursing students, and practicing nurses [5-8]. Given the prediction that new technological advances are expected to transform aspects of nursing and its education [9,10], nurse educators need to increase their knowledge and comfort levels with both the concept and realities to be brought by emerging AIHTs. Additionally, nurses in clinical practice urgently require new knowledge and skills to effectively incorporate AIHTs into their practice [10].

Background

As cited in the *Framework for the Practice of Registered Nurses in Canada*, “nursing knowledge is organized and communicated by using concepts, models, frameworks, and theories” [11]. There are four central concepts in particular that form the metaparadigm of nursing, and they are as follows: the person or client, the environment, health, and nursing [12]. Nurses use knowledge from a variety of sciences and humanities to inform their practice, including biology, chemistry, social and behavioral sciences, and psychology [11]. The integration of AIHTs into nursing education is essential to ensure nurses are adequately equipped with the requisite knowledge to optimize patient health outcomes in an evolving clinical and technological environment.

As emerging AIHTs modify health practices, health professionals will need to adapt their current ways of practicing to operationalize these technological advances [13]. Therefore, it is important for nurses to understand how AIHTs can be integrated into the conceptual foundation of nursing practice as they cocreate new models, frameworks, and theories that may be required to support the emerging technologies. This is particularly important given the increasing usage of AIHTs to

enhance clinical decision making [14] and their potential to influence the traditional nurse-patient relationship.

Machine learning (ML), a subset of AI, uses algorithmic methodologies and techniques to process information in ways that can imitate human decision making [1]. Predictive analytics is a “branch of data analytics that uses various techniques, including ML, to analyze patterns in data and predict future outcomes” [15]. Clinical decision support systems that use AI-powered predictive analytics and ML algorithms to assist nurses in making clinical decisions for their patients based on trends in data are currently being used in clinical practice [16,17]. Similarly, virtual avatar apps that integrate chatbot technology to simulate interactive human conversations between health professionals and patients are growing in popularity [18,19]. Furthermore, social robots with natural language processing abilities [20] that enable them to understand, analyze, and manipulate data and generate language [14] are being increasingly used to provide additional companionship for residents in long-term care homes under the supervision of nurses. These technological advances are expected to cause considerable changes to the nursing landscape over the next decade [9], and nursing education as well as nurse educators will be at the forefront of these changes [21].

Current State

Preparing nursing students and nurses for clinical practice in the age of AI requires a balance between teaching for current needs and anticipating future demands [9]. In the last two decades, there have been important accomplishments in nursing informatics that can be leveraged to provide curricular reform support for nurse educators [9]. For example, in 2004, the Technology Informatics Guiding Education Reform (TIGER) initiative was launched in the United States to provide resources to integrate technology and informatics into education, clinical practice, and research [22]. The *TIGER Nursing Informatics Competencies Model* was published in 2009 to support practicing nurses and nursing students [23]. Additionally, in 2012, the Canadian Association of Schools of Nursing (CASN) published the document, *Nursing Informatics Entry-to-Practice Competencies for Registered Nurses* [9,21,24]. Although these resources have been in existence for several years now, it is unclear if educators are effectively applying them and promoting their use [9,21]. A 2017 national survey of Canadian nurses found that the majority of respondents were unfamiliar with the CASN entry-to-practice informatics competencies [25]. According to Nagle et al [21] and Risling [9], one reason for the lack of uptake of these resources may be that a limited number of nurse educators possess the requisite knowledge, skills, and confidence themselves to address students’ learning associated with AI and digital health concepts. Transformation of nursing curricula will be necessary to ensure future nurses are equipped with informatics competencies, as well as competencies in digital and data literacy to work in clinical settings that increasingly use AI and ML technology. Strong nursing leadership will be required to incentivize nurse educators to embrace the need for curricular reform and to adopt new pedagogies that prepare nurses and nursing students to use these emerging technologies [10,26-30].

Objectives

Considering the nascent topic of AIHTs and their influence on the nursing profession, it is important to understand the breadth and depth of literature that currently exists on this topic in order to prepare for future practice considerations. A scoping review was conducted to summarize the findings of four distinct research questions that explore the relationships between nurses, patients, and AIHTs [31]. A scoping review methodology was deemed appropriate for the aims of this project owing to its exploratory nature [32]. Given the number of articles included in the scoping review, a decision was made to divide the results into two standalone papers to improve clarity. This manuscript summarizes the findings of a research question that specifically addressed the current and predicted influences of AIHTs on nursing education. The results of the remaining three research questions have been published separately [33].

Methods

Scoping Review

This scoping review follows the methodological framework developed by Arksey and O'Malley [34] and further advanced by Levac et al [32], which delineates six steps to map the extent and range of material on a research topic [34]. The scoping review methodology helps to provide clarity on what is known and not known on a topic and situate this within policy and practice contexts [35]. The six steps included in the framework are as follows: (1) identifying the research question, (2) identifying relevant studies, (3) selecting the studies, (4) charting the data, (5) collating, summarizing, and reporting the results, and (6) consultation [34]. This scoping review was registered in the Open Science Framework database [36]. A scoping review protocol publication outlining the full methods of this review can be found elsewhere [31]. A steering committee, consisting of a person with lived experience and key stakeholders from various domains of nursing including nursing education, was convened to provide consultation throughout the project [31].

Identifying the Research Questions and Relevant Studies

The research questions were co-developed by project team members and the steering committee. An information specialist was consulted in order to develop an effective search strategy [31]. This review details results from the following research question: what influences do emerging trends in AI-driven digital health technologies have, or are predicted to have, on nursing education across all domains? [31]. The databases of MEDLINE, Cumulative Index of Nursing and Allied Health Literature, Embase, PsycINFO, Cochrane Database of Systematic Reviews, Cochrane Central, Education Resources Information Centre, Scopus, Web of Science, and Proquest were searched for peer-reviewed literature using search strategies developed in consultation with the information specialist (Multimedia Appendix 1). A targeted website search was also conducted for pertinent grey literature, using Google search strings developed by the information specialist. Searches were limited to the last 5 years (ie, January 2014 to October 2019), after it was determined through consultation with the steering

committee that the majority of literature on this emerging topic had been published within this time period [31].

Study Selection

All peer-reviewed and grey literature results were downloaded into EndNote X7.8 (Clarivate Analytics) and imported into Distiller SR (Evidence Partners), a web-based systematic review software program used for screening. A screening guide was developed by two reviewers (CB and LH), and two levels of screening took place [31]. During title and abstract screening, articles were independently assessed by each reviewer and included if they were deemed relevant to the concepts of *AI* and *nursing* [31]. During second-level screening (full text relevance review), reviewers independently assessed each article to ascertain its relevance to one of the four research questions. The Joanna Briggs Institute suggests that when reporting inclusion criteria, they should be based on PCC elements (population, concept, and context) [37]. In terms of the population, articles that discussed nurses, nursing students, or nurse educators, or referred to health professionals more generally were included in this review if the information was relevant to nursing practice [31]. The core concept of this research question was AI and its influence on nursing education; therefore, in order to be included for this question, articles required a clear focus on AI and nursing education. The context and setting of focus included both clinical and academic settings. Finally, owing to the emerging nature of this topic, articles that only briefly discussed nursing education and AI were also included. Conflicts were resolved through discussion and consensus with a third party (RW) [31].

Charting the Data

Standardized data charting forms were created by the two reviewers and tested with a representative sample of articles, with each reviewer independently charting the data [31]. Once consistency in data charting was achieved, data from each included full-text article were charted by one reviewer and verified by the second reviewer to ensure all relevant data were charted. Findings were recorded by study type in separate data charting forms for each research question (ie, qualitative versus quantitative study designs, and expository papers).

Collating, Summarizing, and Reporting the Results

Once all the data from each included article were charted, the findings were summarized in the form of a data package and sent to members of the steering committee for review. Findings were organized by research question, with a table outlining overall descriptive findings of the included studies (ie, number of articles, setting, population, and types of AIHTs discussed). Additionally, categories were identified by the reviewers and outlined in a narrative fashion below the table of descriptive findings for each question.

Consultation

The findings in the summary data package were discussed with the steering committee during two virtual meetings. Feedback was solicited to confirm the categories identified and their applicability or relevance to nursing education.

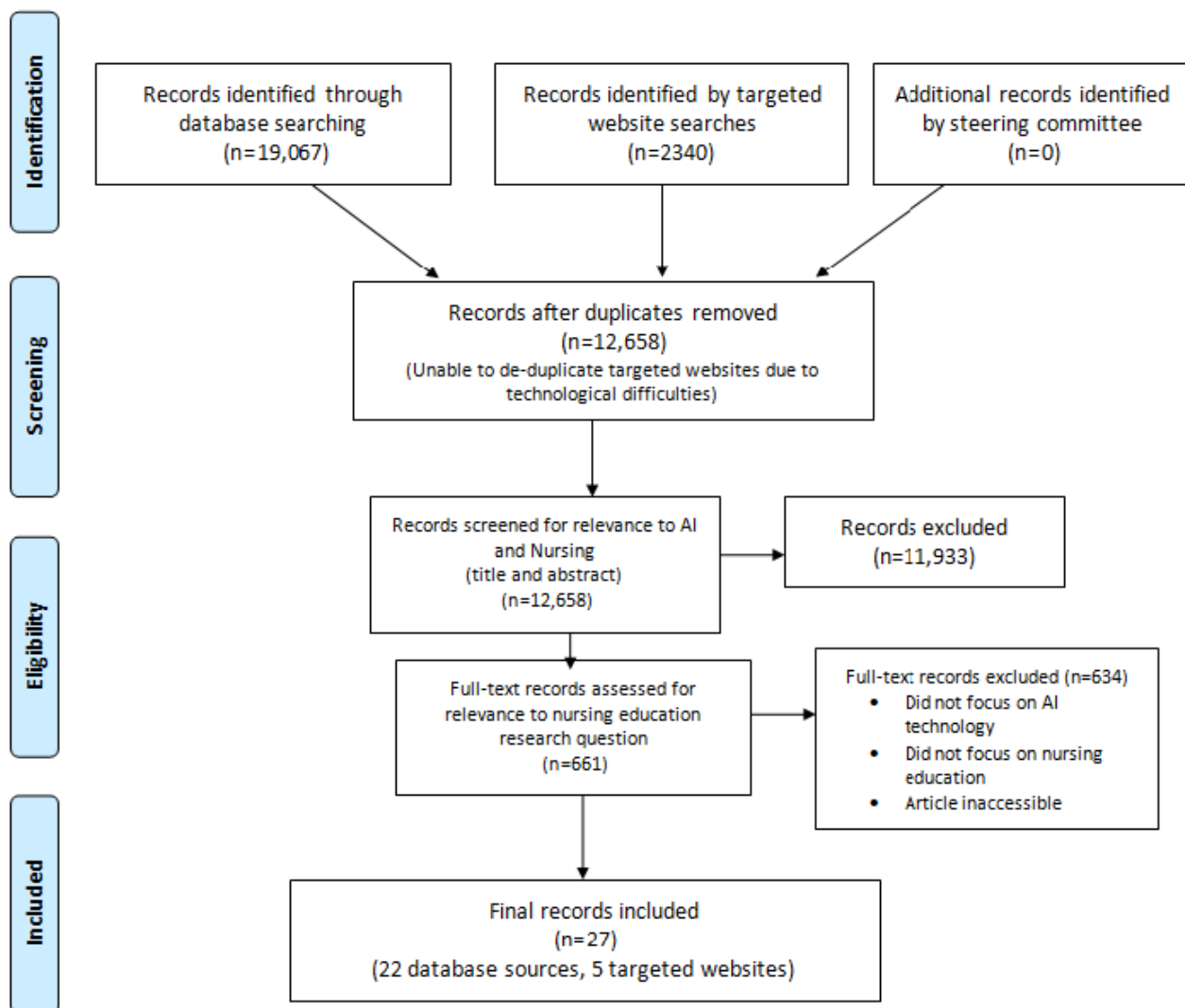
Results

Overview of Articles

A total of 27 articles were included for this research question; these were further characterized as 20 expository papers, six studies with quantitative or prototyping methods, and one qualitative study (see [Figure 1](#) for the full Preferred Reporting

Items for Systematic Reviews and Meta-Analyses [PRISMA] flow diagram [38]). The recipients of education included nursing students at the entry-to-practice, undergraduate, graduate, and doctoral levels, and practicing nurses in clinical settings. Faculty and instructors delivering educational content were referred to as nurse educators, nurse researchers, and nursing leaders. See [Multimedia Appendix 2](#) for further details.

Figure 1. PRISMA flow diagram. AI: artificial intelligence.



The types of emerging AIHTs discussed in the literature that have influenced or are predicted to influence nursing education included the following: virtual avatar apps (ie, chatbots) [7], smart homes [28], predictive analytics [27,39,40], virtual or augmented reality devices [41], and robots [26,42-45]. An overview of these emerging AIHTs and their current or predicted influences on nursing education is provided in [Multimedia Appendix 2](#).

Specific examples of AIHTs that could be used as teaching tools in educational settings were also discussed. These included a face tracker system used to analyze nursing students' emotions during clinical simulations [46] and ML wearable armbands used to measure the accuracy of students' hand washing technique [47]. One article discussed a virtual patient gaming

app used by nurse educators as an interactive teaching tool, providing students with virtual case scenarios congruent with the curriculum objectives [7]. One article encouraged the use of predictive analytics by nurse educators to enhance students' clinical judgment and decision-making skills as they explore the executed decision path provided by the AIHT [40]. Finally, some articles simply presented a broad discussion of AIHTs and their potential influences on nursing education with no mention of specific examples [5,6,8-10,13,29,48-51].

The reviewers categorized the articles into the following two broad groups: (1) influences of AI on nursing education in academic institutions and (2) influences of AI on nursing education in clinical practice. The results of each of these

categories and their subcategories are detailed in the ensuing paragraphs.

Influences of AI on Nursing Education in Academic Institutions

Influences of AI on Nurse Educators

This scoping review revealed a growing trend in the use of AIHTs in nursing education in academic settings, which is expected to greatly increase in the near future. For instance, one article predicted that clinical simulation labs in these settings will have an increased presence of humanoid robots and *cyborgs* to complement their existing high-fidelity simulators [26]. Other emerging AIHTs in clinical simulation labs that were discussed in the literature included *face tracker* software, which uses ML to analyze students' emotions during clinical simulations [46]. Authors noted that this type of technology allows nurse educators to assess the students' emotions at each point of the simulation, along with the time spent on each component of the scenario [46]. The information gleaned through this process enables nurse educators to tailor the simulations to meet the students' needs more effectively [46]. In addition, it was reported that this technology may help students to better understand emotion in their patients [46]. Finally, one article noted that in the foreseeable future, predictive analytics may be used to enhance students' clinical judgment and decision-making skills as they analyze the executed decision path provided by the AIHT [40].

It is also predicted that virtual avatar apps, including virtual patient gaming apps and virtual tutor chatbots, may influence the delivery of nursing education in academic settings as educators use them as teaching tools to simulate interactive clinical scenarios and increase students' comprehension of specific nursing concepts [7,50]. It was identified in the literature that these technologies have the potential to help students improve their communication skills with patients and the interprofessional team and enhance their confidence and self-efficacy prior to entering a real-life clinical environment [7]. Another AIHT that is expected to influence academic settings is a wearable armband that uses ML to evaluate a person's hand washing technique [47]. Authors noted that nurse educators may use this technology to teach nursing students and practicing nurses in clinical settings proper hand washing techniques [47]. Finally, one author suggested that in the age of AI, ML could be used to analyze student data and create personalized learning pathways; this could assist nurse educators with student engagement and retention, and help meet their learning needs [50].

One article stated that the use of AIHTs to support learning in undergraduate nursing programs may positively influence nurses' transition to practice by improving their clinical reasoning skills [41]. It is forecasted that students' exposure to AIHTs in their undergraduate clinical experiences may help prepare them for jobs in technology-rich clinical settings [45]. For example, AIHTs that incorporate virtual or augmented reality provide students with an innovative approach to experiencing the clinical environment [41]. Another article suggested that nursing students are responsive and receptive to

virtual reality education modalities and virtual reality training may be more effective than traditional teaching modalities in some situations [41]. Given these potential benefits, several authors urge nurse educators to consider the value of adopting new pedagogies that provide opportunities for undergraduate nursing students to engage with these emerging technologies [6,10,26-29].

There was minimal literature discussing the influence of AIHTs on the delivery of nursing education at the postgraduate level specifically. One article noted that nursing faculty (ie, at the postgraduate level) will need to know how to use specialized data science methods, and understand how to identify policy trends and implications related to these methods to bring value to nursing science [5]. The authors noted that big data should be used by educators to make nursing knowledge more accessible, visible, visually interesting, and data enhanced [5], both in the classroom and beyond.

The emergence of AIHTs in nursing is predicted to shift nurse educators toward a more multidisciplinary teaching approach (ie, nurses working collaboratively with information technologists, robotics experts, and computer programmers) [26]. One article noted that these types of collaborations have the potential to bridge the skills gaps in nursing and support the advancement of professional groups such as clinical data scientists, medical software engineers, and digital medicine specialists [48], and nurses could then explore these roles.

Influences of AI on Nursing Students

Several articles have highlighted the need for a focused transformation of undergraduate nursing curricula to ensure future nurses are equipped to work in clinical settings that increasingly use AIHTs [6,10,26-29]. Risling [9,49] purports that informatics should be a required nursing competency and that nursing curricula should include core courses on this topic. Others have suggested that nursing curricula should be redesigned to include topics such as data literacy, technological literacy, systems thinking, critical thinking, genomics and AI algorithms, ethical implications of AI, and analysis and implications of big data sets [6,48,52].

Curricular revisions are also delineated in the literature for graduate-level nursing courses to integrate more advanced AI content on topics such as informatics, ethics, privacy, research, and engineering concepts [5,28,39,48,49]. In one article, authors noted that smart homes are expected to influence graduate nursing curricula as they grow in popularity [28]. It is predicted that students will need to understand how AI smart home technology uses sensor data to assist older adults with "aging in place" by monitoring their movement in the home [28].

Changes are also suggested for courses at the doctoral level to provide more in-depth opportunities for nurses to develop competencies in predictive modeling, biostatistical programming, data management, risk adjustment, multivariable regression, ML, governance of big data, and cyberthreats [5,39]. Two universities in the United States have strategically incorporated data science into the core curriculum for their nursing doctoral program [5]. It was noted that the integration of data sciences with nursing theory development will be an

important addition to the curriculum at the postgraduate level in these universities as more AIHTs are being used in the health system [5].

In addition to the need for new AI technological competencies, several authors accentuated the importance of a continued focus on interpersonal human communication skills and empathy in nursing education curricula. This combined focus is deemed necessary to ensure that nurses continue to provide person-centered compassionate care in a health system increasingly being dominated by machines [13,27].

Innovative educational programs that combine biomedical engineering and nursing have been proposed as a way to educate a new cadre of health professionals and increase opportunities for nurses to contribute to the co-design of AIHTs [53]. At the time this scoping review was conducted, no universities had created an entirely new discipline to support the anticipated nursing-AI integration (eg, *nurse-engineering*); however, a few universities had created unique collaborations or joint degrees to improve patient experiences or health system efficiencies with greater use of technology [53].

Influences of AI on Nursing Education in Clinical Practice

The majority of articles in this category focused on the influences of AI on nurses within the hospital setting. However, some publications focused on the influences of AI on nurses in long-term care or home care settings as well. Given the scope of change that AIHTs are likely to engender, authors have recommended that nurse educators in all practice settings provide appropriate professional development education to equip nurses with the requisite knowledge and skills to use these tools in their work environment [8]. It has also been suggested that nurses assume responsibility for upgrading their skills as AIHTs are increasingly deployed in clinical practice settings [10,29,42-44].

It was predicted in the literature that more professional development opportunities (eg, courses and workshops) will be needed in the workplace to support emerging areas of AIHTs [8,29,54] to ensure nurses maintain relevant competencies and skills in their practice setting [10]. One article suggested that nursing informaticians should be utilized to establish a strong foundation of evidence regarding the necessity of nursing data [8], which can be used to inform professional development workshops and nursing clinical competencies. Furthermore, two articles suggested that educational resources be tailored to recipients [48,52]. For example, educational resources to “educate the educators” [48] will differ from those used to train point-of-care nurses in their clinical settings [52], and continued professional development will need to be tailored to those specialists who work more intimately with AIHTs (eg, nursing informaticians) [48,52]. One article suggested that in the clinical setting, examining predictive analytics models can help facilitate knowledge transfer and build capacity in newer less experienced nurses to understand AI’s personalized decision-making process [40].

Discussion

Key Considerations

AIHTs are already beginning to influence the nursing practice, and it is crucial that nurse educators are prepared to equip nurses and nursing students to integrate AIHTs effectively into practice. Considerable curricular reform is needed at all education levels and all designations to support this paradigm shift, and this includes entry-to-practice, undergraduate, graduate, and doctoral education. This reform must ensure that nurses and nursing students are educated on emerging topics that are relevant to AI, based on their roles and responsibilities. Recommended topics of education included the following: basic informatics competencies [8,9,26,28,44], data analytics, predictive modeling and ML principles [5,10,27,39,51,52], engineering principles [26,42,52,53] digital/data literacy [6,48], ethics [5,9,28,48,51,52], privacy issues (including security breaches or “cyberthreats”) [5,9], big data governance [5,48,52], technocentric cultural competence [26], AI research design [28], and robotics care and operations [26,42].

Efforts to align nursing education with this paradigm shift should also include new pedagogies that support emerging AIHTs [6]. Incorporating these technologies into nursing education can increase familiarity and comfort for students when they enter the clinical practice setting [6]. As suggested by Murray [6], the nursing profession is entering an inflection point where AIHTs may enhance various aspects of nursing practice and catalyze much needed changes in contemporary nursing education. Nurse educators, practicing nurses, and students need to remain actively engaged in the planning and implementation of these technologies, thereby enhancing opportunities for their successful integration.

Future State: Nursing Leadership Requirements

Nurse educators in both clinical practice settings and academic institutions have an essential leadership role in preparing nurses and nursing students for a future that will certainly include a wide variety of AIHTs. In order to support a technologically proficient nursing workforce, educators must create a learning environment conducive to nurses evolving their understandings of the novel relationships that exist among nurses, patients, and AIHTs [55]. An important first step will be embedding informatics and digital health technology competencies into all areas of nursing education. A solid understanding of these principles will ensure nurses are equipped to use AIHTs in their clinical practice and, perhaps even more importantly, have the potential to be valuable contributors to the ongoing development of these technologies (ie, co-designers). It has been suggested that the AI industry would benefit from hiring experts from various health disciplines to engage in design processes, and the nursing profession has the potential to provide this expertise [39].

In order to facilitate such a substantial shift, curricula will need to be assessed for their contemporary relevance to health care realities and for their ability to proactively prepare nursing for the future demands of AIHTs [30,56]. One way of accommodating this will be to develop curricula that address the need for a new specialty, the *nurse-engineer* role, to develop

a nurse's role as a co-designer of AIHTs. Undergraduate nursing programs that combine nursing principles with engineering principles can advance the development of AIHTs and help nurses understand the principles behind the AIHTs that they will likely encounter in clinical settings [26,42,53]. The involvement of nurses in co-design of these AIHTs at all stages of design, implementation, and evaluation will reduce the risk of creating technology that burdens health professionals and will help to prevent costly mistakes that arise from lack of clinician input [29,45]. Once again, in order for this to happen, nursing leadership will be required to equip nurses with knowledge and skills in informatics, digital literacy, engineering, and ML in their preliminary nursing education.

Nurses, especially those involved in co-design, must also be prepared to address the nuanced privacy, equity, and ethical implications that will likely arise from the use of AIHTs in nursing practice. Nursing curricula should discuss ethical concerns such as data breaches, the potential for bias in the data used to develop algorithms, and the importance of social justice and person-centered approaches in the design of AIHTs [5,9,30].

In addition to the proposed curricular revisions discussed above, authors also stressed the importance of placing continued emphasis on therapeutic relationships and interpersonal communication in nursing education, as these are core values of nursing care that differentiate nursing from AIHTs [13]. A continued focus on these core nursing values will serve to equip students with the skills necessary to convey compassion and empathy in technology-rich health systems. Nurses and nursing students must begin to reflect on the ways AIHTs may impact nurse-patient interactions and communication patterns between patients, caregivers, and other members of the interprofessional team [13]. Fernandes et al [13] stated, "the transformation of curricula and professional practice focusing on interpersonal and intrapersonal intelligence with attitudes that value human skills will ensure nursing's place/role in a society dominated by machines and scientific progress."

Empowering Nurses and Nursing Students

It has been forecasted that in the immediate future, nurses may use predictive analytics to prioritize educational topics for their patients before discharge [57]. It is also likely that nurses will use virtual avatar apps with chatbot technology to assist in providing patients with additional education, coping strategies, and mental health supports [58]. Building deeper awareness and sensitivity around the implications of these AIHTs through nursing education is a pragmatic first step toward the eventual goal of developing competency and expertise across all domains of nursing practice, and in all settings. This education should be provided in both academic settings (for nursing students) and in clinical practice settings (for practicing nurses) through professional development opportunities such as courses and workshops [8].

Along with building deeper awareness of the topic, nursing students must be empowered to re-envision health practices of the future, as it is clear that these forms of advanced technology will likely change traditional nursing processes and ways of knowing. Furthermore, the emergence of AIHTs demands changes in the usual way of conducting nursing education.

Emerging technologies have accentuated the need for nurse educators to reflect on past practices and transition toward new ways of engaging students [6]. However, in order for new models of nursing education to be successful, both educators and students must be receptive to sizable changes likely to occur with the scaling of AIHTs in all areas of health systems. Subsequently, for nursing education to evolve successfully, both students and educators must appreciate the transformative nature of AIHTs, and their direct and indirect impacts upon all aspects of health delivery and nursing education [26].

While the receptivity of nursing education toward appreciating the growing ubiquity of AIHTs varies among health professionals and educators, ensuring the various fundamental tenets of nursing are not minimized or diluted will be essential moving into the future. For instance, the role of compassionate care within nursing practice should be viewed as an important and requisite feature of all care provided through or with AIHTs that are used by nurses. The nursing profession must not lose sight of its greatest attributes, including compassionate care, in light of a technological future [13]. Concerns related to nurse-patient interactions and therapeutic relationships will be paramount in the years to come, and nurses require the skills to balance human caring needs with technological AI advancements [9]. While technology and nursing are inextricably linked in nursing practice, the caring values espoused by nurses must be protected and amplified through the technology used to support care delivery [44].

Future Research

While discussions about AI are beginning to emerge in the nursing education literature, many of the articles included in this review focused on nursing informatics more generally and briefly mentioned AI. Additionally, as the majority of papers included in this review were expository papers and white papers, there is a need for more research in this context. Further research is needed to continue identifying the educational requirements and core competencies necessary for specifically integrating AIHTs into nursing practice. Future research should also focus on identifying the most effective ways AI can be used as a tool in nursing education.

Limitations

The findings of this review should be interpreted in light of some limitations. Computer science and engineering databases were not searched owing to accessibility issues and organizational licensing restrictions. This limitation may have led to research gaps, and it is recommended that future reviews on the topic of AI and nursing utilize these databases. In addition, only articles published in English were considered for selection and the reference lists of included studies were not searched. This may have led to important articles on the topic being missed. The reviewers did not use Cohen kappa when calculating interrater agreement during title and abstract screening, and instead used percentage agreement (97% agreement). While this was done for feasibility purposes, it is recognized that percentage agreement is not as reliable as Cohen kappa when calculating interrater agreement. Finally, the authors acknowledge the likelihood that more research has been conducted on this topic since performing the original search in

2019; however, owing to feasibility restrictions, it was not possible to perform an updated search.

Conclusions

Nurse educators in clinical practice and academic institutions around the world have an essential leadership role in preparing nurses and nursing students for the future state of AIHTs. It is evident that AIHTs are transforming health systems as they currently exist, and the nursing profession needs to be actively involved in this rapidly evolving process or risk unwanted consequences for both patients and the discipline if this technological revolution proceeds unchecked. Nurse educators need to prepare the profession for a future that in many institutions and settings is already here.

AIHTs are destined to transform health education and delivery, and this process will require education, preparation, and adoption by nurse educators, as well as a strong amount of co-design of these technologies. In collaboration with other

health disciplines, nurses are in an ideal position to lead research on AIHTs. Nurses uniquely understand the complexities of the health environment [45] and can identify the ways patients are best served by technology [49]. A strong educational foundation in AI principles is the first step to ensuring nurses' contribution at all levels of design, implementation, and evaluation of AIHTs.

To our knowledge, this is the first scoping review to examine AIHTs and their influence on nursing education. While there has been research conducted on AIHTs and on nursing education as separate research topics, now is the time to realize the critical relationship between these two entities. AIHTs cannot be implemented in an effective manner without the solid foundation of nursing education, in both academic and clinical practice settings. The findings of this review will help nurse educators across all sectors to proactively shape the nursing-AI interface, ensuring that nursing education aligns with core nursing values that promote compassionate care.

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Conflicts of Interest

None declared.

Multimedia Appendix 1

MEDLINE and targeted website search strategies.

[DOCX File, 721 KB - [nursing_v4i1e23933_app1.docx](#)]

Multimedia Appendix 2

Overview of the findings.

[DOCX File, 24 KB - [nursing_v4i1e23933_app2.docx](#)]

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Abbreviations

AI: artificial intelligence
AIHT: artificial intelligence health technology
CASN: Canadian Association of Schools of Nursing
ML: machine learning
TIGER: Technology Informatics Guiding Education Reform

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