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REVIEW

The Digital Hospital: A Scoping Review of How Technology Is Transforming Cardiopulmonary Care

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Background Innovative models of health care that involve advanced technology in the form of a digital hospital are emerging globally. Models include technology such as machine learning and smart wearables, that can be used to integrate patient data and improve continuity of care. This model may have benefits in situations where patient deterioration must be detected quickly so that a rapid response can occur such as cardiopulmonary settings.

Aim The purpose of this scoping review was to examine the evidence for a digital hospital model of care, in the context of cardiac and pulmonary settings.

Design Scoping review.

Data sources Databases searched were using PsycInfo, Ovid MEDLINE, and CINAHL. Studies written in English and containing key terms related to digital hospital and cardiopulmonary care were included. The Joanna Briggs Institute methodology for systematic reviews was used to assess the risk of bias.

Results Thirteen (13) studies fulfilled the inclusion criteria. For cardiac conditions, a deep-learning-based rapid response system warning system for predicting patient deterioration leading to cardiac arrest had up to 257% higher sensitivity than conventional methods. There was also a reduction in the number of patients who needed to be examined by a physician. Using continuous telemonitoring with a wireless real-time electrocardiogram compared with non-monitoring, there was improved initial resuscitation and 24-hour post-event survival for high-risk patients. However, there were no benefits for survival to discharge. For pulmonary conditions, a natural language processing algorithm reduced the time to asthma diagnosis, demonstrating high predictive values. Virtual inhaler education was found to be as effective as in-person education, and prescription error was reduced following the implementation of computer-based physician order entry electronic medical records and a clinical decision support tool.

Conclusions While we currently have only a brief glimpse at the impact of technology care delivery for cardiac and respiratory conditions, technology presents an opportunity to improve quality and safety in care, but only with the support of adequate infrastructure and processes.

Protocol Registration Open Science Framework (OSF: DOI 10.17605/OSF.IO/PS6ZU).

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Keywords Artificial intelligence • Cardiopulmonary • Digital hospital • Digital decision support • Machine learning • Medication error • Patient experience

Introduction

Innovative models of care that integrate innovative technology to improve patient outcomes, streamline operations, deliver high-quality care, and improve work conditions for staff are emerging globally [1–3]. One model of care, a digital hospital, is showing promise to improve workflow and reduce errors within a hospital setting [1]. This model can involve machine learning (ML) and artificial intelligence (AI), sensors, blockchain technology and smart wearables for tasks such as automation of administrative and workflow processes, diagnostics, and patient communication. For example, electronic patient data can be seamlessly integrated with patient records, updated frequently and aggregated across time points, thereby increasing clinical access [4]. Digital hospitals offer many benefits that include improved continuity of care, utility of hospital beds [5], patient engagement [2,5], patient safety [1,2,5], organisational processes [6], predictive and diagnostic medicine [6,7], a reduction in the cost of care [6–8] and administrative burden [6,9]. They also have been reported to facilitate personal medicine [1,8], remote care [6,9], and quality improvement [7,8]. Two clinical areas where technology might be leveraged to improve patient care and workflow are the assessment and treatment of cardiac and pulmonary conditions.

Digital Hospitals in Cardiopulmonary Settings.

A digital hospital could be enormously beneficial in a cardiology setting, where a patient's condition can deteriorate quickly, and rapid decisions are critical. There is a concerning survival rate, post-in-hospital cardiac arrest, for out of usual working hours of 15%–20% [10]. Survival of an in-hospital cardiac arrest is largely dependent on early detection, a rapid high-quality resuscitation response, and high-quality post-resuscitation care [10]. Additionally, patients who present to an emergency department with chest pain need to be assessed rapidly to rule out a significant event such as myocardial infarction, and so that alternative causes can be considered [11]. A digital hospital that offers predictive and diagnostic medicine [6,7] and improved patient safety [1,2,5], could add significant value to in-hospital acute cardiac conditions.

Pulmonary conditions also represent a significant burden on health systems worldwide. An estimated 339 million people suffer from asthma [12] and 65 million people are diagnosed with moderate to severe chronic obstructive pulmonary disease (COPD) [13], and the prevalence of both is increasing. In a review of the literature, Ding et al. [14] reported that technology has been used along the COPD patient journey and reported including self-management, in-hospital, and hospital in the home (HITH) in the form of home care programs, electronic medical records (EMR), big data analytics and monitoring. However, their review was not systematic and may have missed some critical work in the area, particularly in relation to the role of technology in the hospital setting. In a systematic review, Unni et al. [15] reported that technology integrated into asthma interventions (e.g., education, self-management) shows some benefit for patient outcomes (e.g., medication adherence). However, the role of technology in the hospital care delivery context for pulmonary conditions is not yet clear. It is likely that technology integrated into the hospital setting for diagnostics, monitoring, treatment and management interventions could improve patient outcomes and mitigate the growing burden that pulmonary conditions will place on health services.

Digital Hospitals and Human Factors

A digital hospital could be beneficial from a human factors perspective as it can reduce human error and relieve burdensome, administrative tasks for clinicians [6,9]. For example, the use of ML assistive tools which perform tasks such as robotic complex surgical procedures [16], medical image interpretation [17], and image classification [18]. It has been suggested that tasks that are automated are efficient and reduce cognitive demand [19]. While there is a crucial balance between too much and not enough cognitive demand for optimal human performance [20], if demands are too high (as is often the case in hospital settings), human performance will deteriorate over time as resources to acquire, interpret and process information are depleted [21]. Automation of tasks via a digital hospital model could alleviate cognitive burdens and free up resources for other important tasks.

While implemented on a small scale, advanced technology in the form of a digital hospital is an emerging model of care. Given the significant advantages of a digital hospital being implemented in cardiopulmonary settings, it is important to examine the evidence for this model. The purpose of this scoping review was to examine the research evidence for a digital hospital model of care, in the context of cardiopulmonary settings.

Methods

This review originated from a large integrative review that identified innovative models of care reported in the grey and academic literature. The protocol for the integrative review has been registered with Open Science Framework (OSF: DOI 10.17605/OSF.IO/PS6ZU). For the grey literature review, two reviewers reported on 82 articles that met the

Table 1 Academic search string.

Condition	
Acute	"cardiac arrest" OR "chest pain" OR "myocardial infarction" OR "heart attack" OR "pneumonia"
OR	
Chronic	"congestive heart failure" OR "chronic heart failure" OR "COAD" OR "COPD" OR "asthma" or "chronic obstructive pulmonary disease" OR "chronic obstructive airway disease"
AND	
Model of Care	
Digital hospitals	"digital hospital$" OR "smart hospital$" OR ("artificial intelligence" and "hospital") OR "paperless hospital" OR "learning hospital$" OR "digital healthcare" OR "learning health system" OR "digitised health service$" OR "automated"

inclusion criteria. Seven themes were deductively identified to group models of care, including digital hospitals. The focus of this review is on digital hospitals in the context of cardiac and pulmonary conditions, and therefore only those papers are reported. As the integrated review was commissioned to inform the development of a new hospital in Western Sydney, an analysis of the prevalent conditions in the catchment was undertaken. As such, this review is focussed on the conditions listed in Table 1.

Search Strategy

For the integrative review, a comprehensive search strategy was developed and three academic databases were searched: PsycInfo, Ovid MEDLINE, and CINAHL in June 2021, and updated in May 2022 and March 2023, using multiple terms to identify the models of care and acute and chronic conditions. The grey literature search strategy involved an advanced Google search and targeted hand searching of relevant websites (e.g., Organisation for Economic Co-operation and Development [OECD], World Health Organization, Kings Fund, Accenture, World Economic Forum). Table 1 presents the academic search string, relevant to digital hospitals, cardiology and pulmonary.

Study Selection

Inclusion and exclusion criteria included empirical, peer-reviewed studies in English between the years 2016–2023. The integrative review sought evidence for models of health care with priority conditions. Included studies had to provide an analysis of an intervention compared to usual care, or the feasibility of the model. Papers must include care delivered in a hospital rather than in a virtual environment. Protocol papers, COVID-19 focussed papers, and cost-focussed papers were excluded. Studies that reported evidence for tool validation during the pre-implementation stage were also excluded.

The screening of the integrative academic literature involved the pairing of 16 reviewers who were each allocated 926 articles for screening the title and abstracts. For the full-text screen, all articles were blind reviewed for inclusion, methodological quality, and data extraction, and discrepancies were discussed within pairs. The current review sought out evidence for the digital hospital model of care for cardiac and pulmonary conditions.

Risk of Bias

The methodological quality of included studies was undertaken on all articles that were included following full-text screening. The quality assessment was conducted using the Joanna Briggs Institute (JBI) Critical Appraisal Checklist for Systematic Reviews and Research Syntheses [22]. Tools were selected based on study design. Quality was assessed by independent pairs, and discrepancies were resolved via discussion.

Data Processing and Analysis

Due to heterogeneity in study design, sample, and outcome measures of the included studies, a narrative synthesis was performed. The synthesis included numerical and textual summaries.

Patient and Public Involvement

Patients and public were not involved in the design or conduct of this review.

Results

Study Selection

The two-step screening process for the academic literature included: the title/abstract screen (8,416 articles) and the full-text screen (105 articles). Nine primary studies were identified from other sources (systematic review). A total of 3,345 duplicates were removed and 8,311 articles were excluded at the title/abstract screening stage, and 92 at full-text screening. Common reasons for exclusion were the lack of an evaluation of the models of care (5,632), the absence of a priority condition including cardiac or pulmonary conditions (911) and that the article was a protocol for a study (483) In addition, articles that focussed on COVID-19, cost-effectiveness, or did not present evidence of implementation in a health facility, were removed. Studies were excluded after discussion with the broader research team (AC, EA), who assessed and agreed upon the quality appraisal and inclusion of the studies. These criteria yielded seven articles addressing cardiac conditions and six articles addressing pulmonary conditions which were

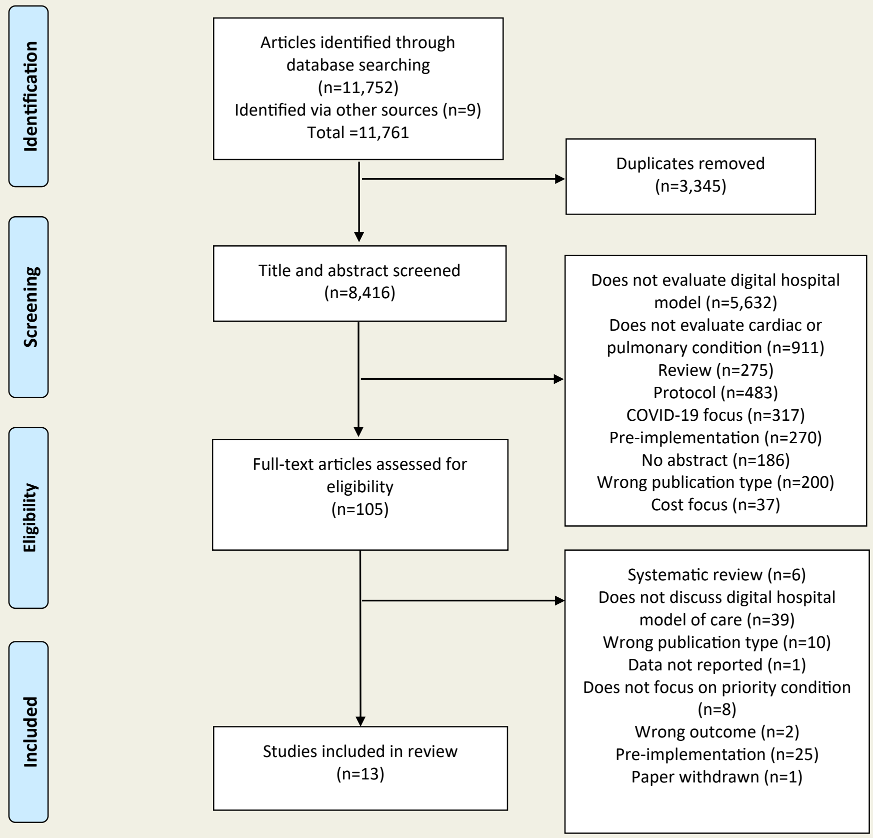

Figure 1 Systematic review flowchart.

obtained using the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) process [23]. Figure 1 illustrates the process by which studies were selected for review.

Description of the Included Studies

Cardiac

After the full-text screening, seven were included in the final review and they covered cardiac arrest (four), and clinical deterioration (three). The articles were published between 2018 and 2022 and evaluated quantitative (seven) evidence. Included articles described research conducted in the USA (two), South Korea (two), China (two) and Taiwan (one).

Most of the studies reported ML algorithms such as decision support as the intervention [24–26], to assess their efficacy and feasibility compared to usual systems. Yen et al. [27] reported a combination of telemedicine and feedback reporting as the intervention to improve patient clinical outcomes and usability.

Pulmonary

After the full-text screening, six studies were included in the final review covering ventilation (two), asthma (two), pneumonia (one) and COPD (one). The articles were published between 2016 and 2022 from research conducted in USA (five) and Brazil (one).

One study reported a natural language processing (NLP) algorithm for asthma criteria to enable automated chart review using EMR [28]. Brown et al. [29] reported a computer-based physician order entry electronic health records intending to improve prescription errors, and Press et al. [30] reported inpatient virtual education which aimed to reduce health care utilisation. Kassis et al. [31] reported on adaptive support ventilation which aimed to delivery tidal volume based on respiratory mechanics. Table 2 provides an overview of the included studies.

Quality Assessment

The included studies were assessed independently as having potential flaws or limitations in design, conduct or analysis that could distort the results (see Table 3).

Layout of Findings

For each of the studies, we extracted data on health care utilisation, clinical indicators and mortality, patient knowledge, and additional outcomes such as physician involvement in care and the impact of technology on determining clinical status. Figure 2 presents the interventions and

Table 2 Description of included studies striated by condition.

Cardiac Conditions					
Author, Year, Country	**Study design**	**Type of digital hospital**	**Characteristics and factors reported**	**Period of study**	**No. of Participants**
Cho et al. 2020 [24], South Korea	Retrospective cohort study	Deep learning-based early warning system	Compared the effect of a deep learning-based early warning system with conventional warning systems used in hospitals, such as modified early warning score and single parameter track and trigger system in predicting in-hospital cardiac arrests	12 months	8,039
Gao et al. 2022 [32], China	Retrospective cohort study	Automated cardiopulmonary resuscitation	Compared the efficacy of automated cardiopulmonary resuscitation and manual cardiopulmonary resuscitation	24 months	106
Green et al. 2018 [25], USA	Retrospective cohort study	Deep learning-based early warning system	Compared the "Between the Flags" calling criteria to MEWS, NEWS and early warning risk scores (eCART) for detecting clinical deterioration	60 months	107,868
Jerng et al. 2022 [33], Taiwan	Retrospective cohort study	Decision support alerting mechanism	Assessed the effect of decision support linked rapid response system on detecting clinical deterioration	Stage 1: 60 months Stage 2: 90 months	7,281
Oh et al. 2018 [26], South Korea	Retrospective cohort study	In-hospital rapid response system	Assessed whether a rapid response system reduced the incidence of in-hospital cardiopulmonary arrest for postoperative patients	Pre intervention=57 months. Post-intervention=51 months	Pre intervention n=95,197 Post-intervention n=111,857
Winslow et al. 2022[34], USA	Before and after study	Electronic Cardiac Arrest Triage (eCART)	Determine the early warning risk score (eCART) on mortality for elevated risk adult in inpatient settings	Baseline=10 months; Intervention= 10 months	Baseline=3,191; Intervention=3,490
Yen et al. 2021 [27], China	Retrospective cohort study	Wireless real-time ECG telemonitoring system	Assessed the effect of continuous telemonitoring with a wireless real-time ECG on the prognosis of resuscitated in-hospital cardiac arrest patients and compared the resuscitation outcome of the continuous ECG telemonitoring group to the general care group (i.e., regular vital signs recording and conscious level check-up; additional bedside ECG and blood pressure monitoring where required)	47 months	115

Pulmonary Conditions					
Author, Year, Country	**Study design**	**Type of digital hospital**	**Characteristics and factors reported**	**Period of study**	**No. of Participants**
Brown et al., 2016 [29], USA	Before and after study	Computer-based physician order entry electronic health records	The effect of a computer-based physician order entry set in reducing prescribing errors, types of errors, hospital length of stay, unscheduled visits, rehospitalisation and 30-day mortality, compared with pre-implementation for chronic obstructive airway disease	18 months	194
Dean et al. 2022 [35], USA	Cluster controlled	Electronic pneumonia clinical decision support tool	Evaluate the electronic pneumonia clinical decision support tool, embedded within the electronic health record	36 months	6,848
Kassis et al. 2022 [31], USA	Crossover, randomised comparative	Adaptive support ventilation	The accuracy of automated adaptive support ventilation compared to standard-of-care lung protective ventilation strategy	33 months	17
Press et al., 2020 [30], USA	Randomised control trial	Inpatient virtual education	The feasibility of a virtual education approach in improving inhaler technique for asthma patients, compared with in-person education on inhaler technique and health care utilisation.	1 month	118
Ratti et al. 2022 [36], Brazil	Prospective, randomised comparative	Inspiratory muscle electronic training strategies	Compare inspiratory muscle electronic training with spontaneous breathing with a T-piece in tracheostomised patients on weaning time or successful weaning rates	37 months	132
Wi et al., 2018 [28], USA	Retrospective cohort study	A NLP algorithm for asthma criteria	Validated an NLP algorithm for ascertaining asthma status for early identification of children with asthma, compared with manual chart review.	12 months	297

Abbreviations: ECG, electrocardiogram; USA, United States of America; NLP, natural language processing.

Table 3 Results of the quality assessment.

Reference	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9	Q10	Q11	Q12	Q13
Randomised Controlled Trials													
Reference	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9	Q10	Q11	Q12	Q13
Kassis et al. 2022	Y	N	Y	U	N	N	Y	Y	Y	Y	Y	Y	Y
Press et al. 2020	Y	Y	Y	N	N	U	Y	Y	Y	Y	Y	Y	Y
Cohort Studies													
Reference	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9	Q10	Q11		
Cho et al. 2020	Y	Y	Y	Y	U	Y	Y	Y	Y	U	Y		
Gao et al. 2022	Y	Y	Y	Y	Y	N	Y	NA	NA	NA	Y		
Green et al. 2018	Y	Y	Y	N	NA	Y	Y	Y	Y	NA	Y		
Oh et al. 2018	Y	Y	Y	Y	Y	Y	Y	Y	Y	NA	Y		
Wi et al. 2018	Y	Y	Y	U	U	Y	Y	NA	NA	NA	Y		
Yen et al. 2021	Y	Y	Y	U	Y	NA	Y	NA	Y	NA	Y		
Quasi-Experimental Study													
Reference	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9				
Brown et al. 2016	Y	Y	Y	N	Y	Y	Y	Y	Y				
Dean et al. 2022	Y	U	U	N	Y	Y	Y	Y	Y				
Jerng et al. 2022	Y	U	Y	Y	Y	Y	Y	Y	Y				
Ratti et al. 2022	Y	N	Y	Y	Y	Y	Y	Y	Y				
Winslow et al. 2022	Y	Y	Y	Y	Y	Y	Y	Y	Y				

Numbers vary according to study type.
Abbreviations: Q, question; N, no; NA, not applicable; U, unclear; Y, yes.

systems tested in a continuum according to the level of manual human operation of the technology.

Health Care Utilisation

Cardiac

Yen et al. [27] assessed the impact of digital hospitals on health care utilisation; There were no effects on survival to discharge or 24-hour post-event survival, for patients with hypertension; key findings of this paper are provided in Table 4.

Pulmonary

Three studies assess the impact of technology within the hospital context on aspects of health care utilisation including the number of patients accessing acute care in the emergency department after 30 days [30], length of stay for patients with COPD [29], and a reduction in urgent care visits for patients with COPD or asthma for patients who received a virtual education module about inhaler techniques [30]. Although for patients with pneumonia, there was a reported increase in emergency department discharge, there was no change in 7-day hospital readmission rates [35] for a clinical decision support system (see Table 4).

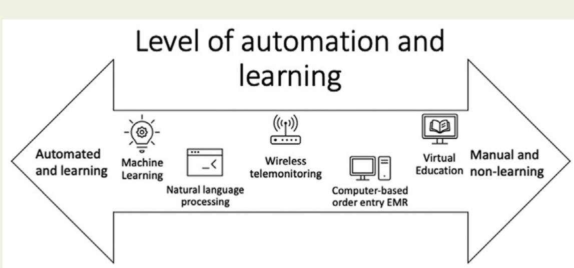

Figure 2 The continuum of concepts and systems tested in the included papers.
Abbreviation: EMR, electronic medical records.

Clinical Indicators and Mortality

Cardiac

Six papers assessed the impact of digital hospitals on clinical indicators and mortality for cardiac conditions; key findings of these papers are provided in Table 5. For example, a rapid response early warning system was more sensitive than conventional methods for cardiac arrest [24]. Gao et al. [32] reported higher rate of resuscitation, and 24-hour survival and discharge rate for automated cardiopulmonary resuscitation (CPR) compared with manual CPR. Yen et al. [27] showed that continuous, bedside telemonitoring resulted in a higher rate of initial success of resuscitation and a 24-hour rate of survival. However, no significant effects were found on survival to discharge rates.

Pulmonary

Four studies assessed the impact of technology within the hospital context on clinical indicators; the key clinical

Table 4 Summary of the papers assessing the impact of digital hospitals on health care utilisation.

Reference	Condition	Finding
Cardiac Conditions		
Reference	**Condition**	**Finding**
Yen et al. (2020)	Cardiac arrest	There were no significant differences observed between the monitored and non-monitored groups in survival to discharge (21.9% vs 16.7%, p=0.498), or 24-hour survival past event after adjusting for covariates.
Pulmonary Conditions		
Reference	**Condition**	**Finding**
Brown et al. (2016)	COPD	The length of time patients stayed in hospital was reduced from 4 days before implementation of an electronic order set to 2.9 days after implementation (p=0.002). There was no effect on unscheduled physician visits, urgent care visits, rehospitalisation, or deaths.
Dean et al. (2022)	Pneumonia	An electronic, open loop, clinical decision support integrated within the electronic health record resulted in a significant increase in outpatient disposition from the emergency department (29.2% to 46.9%; p=0.036). No change in 7-day secondary hospital admission (5.2 vs 6.1%; p=0.31).
Press et al. (2016)	Asthma; COPD	There was a smaller percentage of the virtual teach-to-goal (TTG) group (24%) that required acute care emergency department or hospital utilisation compared to 29% of the in-person TTG group. However, the difference was found not to be significant ($p>0.05$).

Abbreviation: COPD, chronic obstructive pulmonary disease.

indicator finding of this paper is provided in Table 5. The digital hospital model of care resulted in fewer prescribing errors for COPD [29], a reduction in 30-day all-cause mortality for pneumonia [35], and larger tidal volume for acute respiratory distress syndrome [31] (see Table 5).

Patient Knowledge

Pulmonary
One study assessed the impact of technology within the hospital context on patient knowledge; the key finding of this paper is provided in Table 6. There were similar improvements in inhaler technique proficiency for virtual delivery of education and face-to-face education delivery [30].

Additional Outcomes

Cardiac
One paper assessed the impact of digital hospitals on additional outcomes; key findings of this paper are provided in Table 7. Digital hospitals resulted in a reduction in the number of physician examinations [24].

Pulmonary
Four studies assess the impact of technology within the hospital context on determining pneumonia, asthma, COPD, and all-cause mortality status; key findings of these papers are provided in Table 7. The digital hospital model of care reported high predictive values for sensitivity, specificity, and positive and negative predictive values and resulted in faster ascertainment of asthma status compared with a chart review of EMR by data abstractors [28], an increase in concordant prescribing and a reduction in time from emergency department admission to first antibiotic [35], a reduction in prescribing errors [29], and more transfers to ICU after score elevations were noted [34] (see Table 7).

Discussion

This review examined the research evidence provided in grey and peer-reviewed literature identifying the characteristics of an innovative model of health care, digital hospitals, in the context of cardiology and pulmonary specialties. Seven studies were identified as reporting a digital hospital in cardiac care and six in pulmonary care. This review found significant benefits for the use of ML algorithms as an early warning system for cardiac arrest for patients in acute cardiac care [24] and for predicting clinical deterioration using a decision support-linked rapid response system [33]. An electronic cardiac arrest triage score increased ICU admissions and a reduction in all-cause mortality [34].

For pulmonary conditions, the digital hospital model of care had a significant benefit in reducing the length of hospital stay [29] and the number of prescription errors [29,35] as well as the potential to reduce urgent care visits [30]. Virtually delivered patient education provides a feasible alternative to usual care for asthma, increasing inhaler technique proficiency to the same extent as face-to-face education. This review found significant benefits for the use of

Table 5 Summary of papers assessing the impact of digital hospitals on clinical indicators and mortality.

Reference	Condition	Finding
Cardiac Conditions		
Reference	**Condition**	**Finding**
Cho et al. (2020)	Cardiac arrest	An artificial intelligence, deep learning based, rapid response early warning system for predicting patient deterioration leading to cardiac arrest had up to 257% higher sensitivity than conventional methods.
Gao et al. (2022)	Cardiac arrest	Successful return of spontaneous circulation and rate of resuscitation, 24-hour survival and discharge rate were significantly higher for the automated CPR compared with manual CPR ($p<0.05$).
Jerng et al. (2022)	Cardiac arrest	Significant reduction in in-hospital resuscitations and mortality for a decision support-linked rapid response system compared to a standard rapid response system ($p<0.017$).
Oh et al. (2018)	Cardiac arrest	A rapid response system reduced the incidence of in-hospital cardiopulmonary arrest for postoperative patients compared to when not operational (0.56 vs 0.86; $p=0.027$).
Winslow et al. (2022)	All-cause mortality	Hospital mortality was significantly lower using an electronic cardiac arrest risk triage score (8.8% vs 13.9%; $p<0.01$), compared to baseline.
Yen et al. (2021)	Cardiac arrest	No difference was seen between the monitored and non-monitored groups for survival to discharge ($p=0.498$). More patients in the monitored group (49.3%) survived for 24 hours than in the non-monitored group (26.2%) ($p=0.015$). Initial success of resuscitation was significantly greater in the monitored group compared to the non-monitored group (67.1% vs 40.5%, $p=0.005$). The duration of cardiopulmonary cerebral resuscitation (CPCR), which is associated with better outcomes of survival to discharge, was slightly improved in the monitoring group compared to the non-monitoring group (29.1 ± 28.8 min vs 38.7 ± 26.8 min, $p=0.079$).
Pulmonary Conditions		
Reference	**Condition**	**Finding**
Brown et al. (2016)	COPD	The number of hospitalisations with zero prescription errors increased from 18.6% before implementation to 54.3% after implementation of an electronic order set ($p<0.001$).
Dean et al. (2022)	Pneumonia	An electronic, open loop, clinical decision support integrated within the electronic health record reduced 30-day all-cause mortality (odds ratio 0.62, $p<0.001$).
Kassis et al. (2022)	Acute respiratory distress syndrome	Automated adaptive support ventilation provided marginally larger tidal volume corrected for ideal body weight compared to a standard-of-care lung protective ventilation strategy (6.3 mL/kg vs 6.04 mL/kg; $p=0.035$).
Ratti et al. (2022)	Non-spontaneous breathing	Electronically assisted inspiratory muscle training recorded lower scores on the acute physiology and chronic health evaluation scale ($p=0.02$), higher weaning success rates (75%), lower pressure ($p<0.001$), power ($p=0.003$), and energy values ($p=0.003$), compared with a T-piece in tracheostomised patients.

Abbreviations: CPR, cardiopulmonary resuscitation; COPD, chronic obstructive pulmonary disease.

a NLP algorithm, reducing the time taken to ascertain asthma status, thereby improving patient safety and workflow [28]. However, there was no significant effect on unscheduled physician visits, urgent care visits, rehospitalisation, or deaths for COPD patients when a computer-based physician order entry set was utilised [29]. While different approaches have been used in the implementation of the digital hospital model of care for cardiology

Table 6 Summary of the study assessing the impact of Digital Hospitals on patient knowledge.

Reference	Condition	Finding
Press et al. 2020	Asthma; COPD	Virtual-delivered patient-directed education increased inhaler technique proficiency to the same extent as face-to-face education. Performance declined by the same amount for both delivery methods one month after discharge.

Abbreviation: COPD, chronic obstructive pulmonary disease.

Table 7 Summary of the paper assessing the impact of digital hospitals on additional outcomes.

Reference	Condition	Finding
Cardiac Conditions		
Cho et al. (2020)	Cardiac arrest	A reduction in the number of patients who needed to be examined by a physician by 69.2%. Each physician had to examine 20.4 fewer patients compared with standard care to detect one deteriorating patient.
Pulmonary Conditions		
Brown et al. (2016)	COPD	Mean prescribing errors decreased from 1.76 to 0.65 ($p<0.001$) post implementation of an electronic order set
Dean et al. (2022)	Pneumonia	An electronic, open loop, clinical decision support integrated within the electronic health record resulted in a significant increase in concordant prescribing (83.5% to 90.2%; $p<0.001$), and a reduction in the mean time from emergency department admission to first antibiotic (150.9 min vs 159.4 min; $p<0.001$).
Wi et al. (2018)	Asthma	The NLP-PAC showed high sensitivity, specificity, positive predictive value, and negative predictive values (92%, 96%, 89%, and 97%, respectively) when using manual chart review as the gold standard.
Winslow et al. (2022)	All-cause mortality	Compared to baseline, significantly more patients transferred to ICU after first elevated electronic cardiac arrest risk triage score. Within two hours, patients were more than twice as likely to have lactate ordered and have their vital signs reassessed. The number of new code status orders increased (9.8% to 17.5%; $p<0.001$).

Abbreviations: COPD, chronic obstructive pulmonary disease; NLP-PAC, natural language processing-predetermined asthma criteria.

and pulmonary, both approaches aim to reduce human error and improve patient outcomes.

Artificial Intelligence and Health Care

Artificial intelligence (AI) is advantageous due to its capability to process large amounts of health data. This is especially useful for predicting the risk of a future negative event. ML algorithms predict outcomes using historical data and NLP predicts outcomes using language-based data. The use of AI in digital hospitals has significant implications for the quality and safety of care, especially given the need for a rapid diagnosis and response in the event of clinical deterioration. For example, identifying patients with asthma currently requires a manual chart review based on existing predetermined criteria [37]. However, there are no standardised diagnostic criteria for asthma, or asthma ascertainment process, which leads to inconsistent results. Similarly, one of the main issues identified with current rapid response systems for cardiac arrest is their failure to detect signs of clinical deterioration. This is critical as post-arrest survival to discharge rates are less than 20% [10]. Increasing implementation of EMR systems has afforded the establishment of large clinical datasets for epidemiological investigations. Consequently, leveraging AI now has the potential to improve the quality and safety of care delivered in hospitals.

Artificial intelligence based on ML, in a rapid response system, can accurately predict clinical deterioration [24,25,32–34]. Cho and colleagues [24] showed the sensitivity of a deep learning based early warning system was 257% higher than conventional methods. The model accurately predicted patient in-hospital cardiac arrest and unexpected intensive care admissions by analysing patients' vital signs. While the authors acknowledged that future clinical trials and measures of outcomes over a longer period are needed, this could have a significant impact on care given that survival of an in-hospital cardiac arrest is dependent on early detection.

Natural language processing algorithms based on EMR data can reduce delays in diagnosis and time to therapeutic intervention for asthma [28]. Wi and colleagues [28] demonstrated the high sensitivity, specificity and predictive value (positive and negative) of the algorithm compared with manual chart review. The risk factors for asthma identified by the algorithm were comparable to those identified manually by chart review. Wi and colleagues demonstrated the adaptability of the NLP algorithm across multiple sites, providing a platform for standardising asthma definitions. While the technology implemented into hospitals needs to be interfaced across the hospital system to achieve the full benefit of improvements in workflow and patient safety [38], these models have the potential to revolutionise the care experience for patients.

Nine studies reported outcomes post-intervention, two years and greater, which increases the likelihood of their sustainability. Dean et al. [35] reported on a reduction in prescribing errors on a large sample size across 36 months, when aided by automatic decision support, which suggests the findings are robust. Whereas, Winslow et al. [34] measured outcomes ten months post intervention, which may not be long enough to demonstrate effective and stable outcomes over time.

Digital Capabilities and Workload

A digital hospital that implements automation that utilises ML, can reduce human error and relieve burdensome, administrative tasks for clinicians [6,9]. This review identified that a ML based rapid response system for cardiac arrest reduced the number of patients that physicians needed to examine, thereby reducing time pressures and cognitive load [24]. Given that automation reduces cognitive demand [19], this review provides evidence that a digital hospital that implements automated systems that utilise ML could alleviate cognitive burdens and free up physicians' resources for other important tasks.

Strengths and Limitations

The process undertaken in this review was rigorous and comprehensive from a wide range of grey and academic literature resources. Data could not be pooled due to the low number of included studies and heterogeneity of study designs, samples and outcome measures, therefore, a meta-analysis could not be undertaken. All the included studies included a narrow range of conditions such as in-hospital care for cardiac arrest, asthma and COPD, thereby limiting the generalisability to other cardiac issues such as heart failure, and respiratory diseases such as pulmonary hypertension, tuberculosis, and lung cancer. Furthermore, identified studies were sourced from five countries (USA, Brazil, Taiwan, South Korea and China). Differences in health care systems (e.g., governance), resources (e.g., advanced technology availability, distribution), and culture (e.g., attitudes towards technology) may differ in other countries, thereby limiting the generalisability of the review. Future research should focus on the implementation and outcomes of a digital hospital in other governance contexts and cover a range of clinical conditions.

Conclusion

This review identified seven studies that present the digital hospital model of care in the context of cardiology and six in the context of pulmonary conditions. Innovative technological applications were identified that included predictive ML to detect patient deterioration prior to cardiac arrest and to identify at-risk patients, and real-time monitoring as well as virtual delivery of patient education, electronic health records early warning scores, decision support rapid response systems, and algorithms to enable automated chart review using electronic medical records. With the support of adequate infrastructure, implementing these innovations into a digital hospital will improve patient outcomes, management of data, workflow, and workload.

- This study highlights that very few studies have examined and reported the implementation and outcomes of a digital hospital in cardiaopulmonary settings.
- It identifies a gap in the literature and given the benefits of this model reported in other aspects of health care, it is important that future research focusses on cardiac and pulmonary settings.

Declaration of Competing Interests

None.

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Patient Consent for Publication

Not required.

Data Availability Statement

Data can be made available by contacting the corresponding author.

Author Contributions

A.C., E.A. and N.R. conceptualised the study. A.C., N.R. and E.A. contributed to the design of the study. A.C., E.A., N.R., J.H., R.J., U.K. and A.S. performed the data extraction and analysis. A.C. and E.A. drafted the initial manuscript. All authors contributed to the refinement of the paper and approved the final manuscript.

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