Technological Forecasting & Social Change 206 (2024) 123568

Contents lists available at ScienceDirect

Technological Forecasting & Social Change

journal homepage: www.elsevier.com/locate/techfore

Artificial intelligence in acute care: A systematic review, conceptual synthesis, and research agenda

Lea Mareen Meyer[a,*], Susan Stead[a,*], Torsten Oliver Salge[a], David Antons[b]

[a] Institute for Technology and Innovation Management (TIM), RWTH Aachen University, Kackertstrasse 7, 52072 Aachen, Germany
[b] Institute for Entrepreneurship, University of Bonn, Meckenheimer Allee 174, 53115 Bonn, Germany

ARTICLE INFO

Keywords:
Artificial intelligence
Healthcare
Service-dominant logic
Patient journey
Systematic literature review

ABSTRACT

Artificial intelligence (AI) is emerging as a promising healthcare technology. Especially in critical, data-driven, and complex environments such as acute care, the use of AI can significantly improve treatment processes and support clinical staff. To date, AI applications in healthcare are scarce. Research remains fragmented across individual applications. To address this gap, we conduct a systematic literature review. In this review, we map the status quo of AI research in acute care and use service-dominant logic (SDL) from service science as a framework to integrate our analysis. Using a multilayered lens, we (1) identify intended beneficiaries of AI, (2) identify relevant activities supported by AI, and (3) determine those steps of the patient journey that have been in the spotlight for AI research. Our findings suggest that researchers have focused on hospital staff members as intended beneficiaries during the first three steps of the patient journey: admission, diagnosis, and treatment. The patient's perspective, however, remains underexplored. Moreover, 96 % of the research papers we reviewed focus on AI development and proof-of-concept studies, while only 4 % employ and test AI applications in the field. We identify three priorities for future AI research in acute care and provide suitable research methods.

1. Introduction

Acute care – that is, the immediate medical treatment of patients with serious health problems, injuries, or emergencies – is a particularly challenging and high-stakes service setting. Acute care and its subdisciplines, including intensive, critical, emergency, and trauma care, require swift and precise decision-making (Hsia et al., 2010; Hirshon et al., 2013). Resources are often strained, clinical infrastructure and staff are overwhelmed, and time pressure is high. Therefore, the risk of errors and incidents that can harm patients and staff is real (Laxmisan et al., 2007). Shaped by competing institutional logics (Scott et al., 2000), acute care departments and their staff struggle to reconcile quality, cost, and patient experience.

Artificial intelligence (AI) and its applications can potentially support actors in this acute care balancing act (Aleksandra et al., 2024; Chee et al., 2021; Lee and Lee, 2021). Broadly speaking, AI applications can either augment human actors in accomplishing relevant tasks or fully automate these tasks to free up much-needed capacity (Fruehwirt and Duckworth, 2021; Raisch and Krakowski, 2021). The use of AI will reshape acute care processes by improving diagnosis, enabling new screening and treatment opportunities, and supporting time-consuming administrative tasks (e.g., Boonstra and Laven, 2022; Piliuk and Tomforde, 2023). For example, a machine learning (ML)-based speech recognition and transcription system can support the treatment process in the emergency room. It can also help multidisciplinary trauma teams to manage information flows and reduce the reporting burden during the critical early stage of the acute patient journey (Sanchez et al., 2017; Tjardes et al., 2023).

However, AI adoption in acute care remains fragmented (Chee et al., 2021; Kirubarajan et al., 2020). A discrepancy has been noted between the development of AI technology and its clinical implementation (He et al., 2019; Kueper et al., 2020). Major implementation barriers include regulatory or policy hurdles (He et al., 2019; Kelly et al., 2019), a lack of infrastructure and capabilities (Merhi, 2023), and sparse insights about AI's value-creation potential from the perspective of medical staff and patients (Kokshagina, 2021; Paul and Singh, 2023). Research on the design, implementation, use, and effectiveness of AI in acute care is rapidly expanding across disciplines. Still, there is no coherent picture of the body of evidence (Kirubarajan et al., 2020; Okada et al., 2021; Poncette et al., 2020).

* Corresponding authors.
E-mail addresses: meyer@time.rwth-aachen.de (L.M. Meyer), stead@time.rwth-aachen.de (S. Stead), salge@time.rwth-aachen.de (T.O. Salge), antons@uni-bonn.de (D. Antons).

https://doi.org/10.1016/j.techfore.2024.123568
Received 5 October 2023; Received in revised form 24 June 2024; Accepted 25 June 2024
Available online 6 July 2024
0040-1625/

Literature reviews are critically important in this regard. They help synthesize the existing body of evidence, direct future research, and guide clinicians, managers, and policymakers. Prior literature reviews have shown progress in the AI acute care context. However, they typically focus on specific AI use cases, medical conditions, or algorithms (Chee et al., 2021; Choudhury and Asan, 2020). These reviews foregrounded the perspective of clinical staff at the expense of other actors such as patients and their relatives (Aleksandra et al., 2024; Boonstra and Laven, 2022). Therefore, researchers need an integrative, theory-driven review on the role and integration of AI in acute care services. Emphasis must be placed on AI's interactions with clinical staff, patients, and their relatives toward the triple objective of improved quality, efficiency, and patient experience.

Against this backdrop, we draw on service-dominant logic (SDL) as an ideal conceptual framework to provide a comprehensive, human-centric picture of AI's usage in acute care (Vargo and Lusch, 2004, 2008, 2015). As a multi-actor framework from service science, SDL helps to rebalance and integrate the distinct perspectives, associated logics, and goals of all key actors that co-create acute care services (Vargo and Lusch, 2017). When seen through an SDL lens, it is only through interaction with managerial and clinical staff, as well as patients and their relatives, that AI can co-create value (Swan et al., 2023). Deeply grounded in SDL, our systematic literature review helps to (1) identify key actors for AI applications in acute care, focusing on the role of end users, (2) identify relevant activities supported by AI, and (3) determine the relevant patient journey steps where AI is currently used. This allows us to uncover three major gaps in our understanding of the role of AI in acute care that future research must address. Particularly, we encourage future researchers to (1) explore the triadic interaction between beneficiaries and AI applications, (2) examine AI applications to support underexplored patient journey steps, and (3) test AI applications in realistic clinical settings. For each research priority, we offer frameworks and tools from the service discipline suitable for future research.

2. Acute care and the promise of AI

2.1. The institutional complexity of acute care

Healthcare is a complex field shaped by a set of competing and co-evolving institutional logics. These are defined as "*belief systems and associated practices that predominate in an organizational field*" (Scott et al., 2000: 170). Studies from the US (e.g., Ruef and Scott, 1998), Canada (e.g., Reay and Hinings, 2009), and the United Kingdom (e.g. Currie and Guah, 2007) document the coexistence and shifting momentum of a *professional logic* focused on quality of care and embraced mainly by clinical professionals, a *business logic* centered on efficiency and adopted primarily by healthcare managers, and a *market logic* emphasizing patient choice and patient experience advocated by regulators. Fueled by these coexisting logics, healthcare faces the challenge of simultaneously increasing quality, efficiency, and the patient care experience.

Acute care is a highly demanding, resource-intensive area of healthcare tasked with treating the most life-threatening injuries. Thus, it is particularly exposed to these logics (Hsia et al., 2010). Acute care includes various subdisciplines such as intensive care, critical care, emergency care, and trauma care (Hirshon et al., 2013). Clinical processes and decisions in these disciplines take place in a dynamic, complex working environment, often under time pressure (Laxmisan et al., 2007; Roessler et al., 2017). It can be highly challenging under such conditions to simultaneously meet the quality, cost, and patient experience aspirations fueled by the three coexisting logics. Indeed, shifts in these logics can threaten or even disrupt the fragile balance between professional dominance, managerialism, and patient-centricity in the field.

To illustrate this fragile balance, we use two prominent scandals from the English National Health Service as examples. The first focuses on the Bristol Royal Infirmary, where death rates for open-heart surgery among babies were found to be twice as high as expected from 1988 to 1994 (Secretary of State for Health, 2001). Some of these problems were attributed to a shortage of pediatric clinical staff and infrastructure, as well as inadequate oversight, poor communication between groups in the hospital, and a lack of patient-centricity (Weick and Sutcliff, 2003). The second scandal unfolded at Mid Staffordshire Hospitals between 2005 and 2008, where mortality rates were between 27 and 45 % higher than expected. Investigators identified a root cause as a shift of attention away from clinical quality to financial targets. This shift led to the cutting of 150 clinical positions, reduced training expenditures, subsequent understaffing, and skill gaps even in critical areas of acute care (Alexander et al., 2015). The formal investigation report concluded with a call to rebalance competing logics and move patients and their experience to center stage:

"People must always come before numbers. Individual patients and their treatment are what really matter. Statistics, benchmarks, and action plans are tools not ends in themselves. They should not come before patients and their experiences. This is what must be remembered by all those who design and implement policy for the NHS." (Francis, 2010, p.4).

Fortunately, such major scandals are rare in acute care. Accidents, errors, and other unintended, potentially harmful deviations from planned courses of action are more common (Perrow, 1999; Tucker and Edmondson, 2003). These types of accidents and errors can be avoided (e.g., Brodbeck et al., 1993; Norman, 1982; Reason, 1990). They are distinct from operational *problems* which undermine an employee's ability to execute a prescribed task. These problems can stem from the unavailability of something an employee needs in the time, location, condition, or quantity desired or the presence of something that should not be. Either condition can interfere with the execution of the designated task. Examples of such problems are missing supplies or information. Observational studies from healthcare show that the majority of the failures of front-line employees (86 %) were problems rather than errors (Tucker and Edmondson, 2003). The relative visibility and frequency of problems compared to errors make them occur more often in the presence of front-line staff, who can take action to solve them.

2.2. The promise of AI in acute care

Incorporating AI applications in acute care can help to reduce errors, incidents, and other problems, as well as help actors learn from them. Among others, AI applications can support key clinical and managerial processes from admission to diagnosis, treatment, and discharge. They can do so by either augmenting human tasks or automating tasks previously performed by humans (Fruehwirt and Duckworth, 2021; Raisch and Krakowski, 2021). If designed and implemented effectively, AI applications can cater to all three institutional logics and enhance quality, efficiency, and patient experience. Initial evidence demonstrates the potential of AI applications to predict disease, hospital mortality, length of stay, patient re-admission, and discharge (Hanson and Marshall, 2001; Kelly et al., 2019; Mathur and Burns, 2019). It can also reduce the complexity of clinical processes, improve efficiency, optimize resource allocation, and prevent treatment errors (Dervishi, 2020; Dwivedi et al., 2023; Pan et al., 2020; Ye et al., 2020).

Especially in acute care, AI applications and associated research have greatly evolved in recent years (Mathur and Burns, 2019; Piliuk and Tomforde, 2023). The term "AI" was first introduced in 1955 by John McCarthy as a concept describing machines that behave like "intelligent" humans (McCarthy et al., 2006). The analysis and synthesis of how computers can behave intelligently comprise AI (Poole and Mackworth, 2010). It consists of different subdisciplines such as machine learning (ML) and deep learning (DL). According to Kononenko (2001), ML is the most prevalent research subject in AI. By identifying and extracting patterns from data, ML algorithms let computer systems solve real-world problems and augment or even automate human decision-making

(Goodfellow et al., 2016; Murphy, 2012). Systems and algorithms in ML are typically trained on large amounts of data. The trained model can be applied to different datasets with similar structures to generate meaningful insights (Mitchell, 1997). Three methods of data analysis are used in ML: supervised, unsupervised, and reinforcement learning (Antons et al., 2020; Murphy, 2012). In acute care, ML algorithms can be applied to predict treatment outcomes, detect objects in images, and assist in clinical decision-making (Blomberg et al., 2019; Mathur and Burns, 2019).

Deep learning (DL) is a sub-area of machine learning. It uses artificial neural networks to recognize and process complex structures in data at several levels of abstraction (Goodfellow et al., 2016; LeCun et al., 2015). An artificial neural network is a computational learning system that simulates the way a human nervous system processes information through a neuronal network (Nielsen, 2015). Based on experience and data, a neural network enables the autonomous optimization of computer systems. Deep learning (DL) is inspired by the way the human system learns from experiences and understands complex concepts by combining simple ones (Goodfellow et al., 2016; LeCun et al., 2015). It offers the possibility of discovering hidden structures in high-dimensional and complex data (LeCun et al., 2015). In acute care, DL systems are used to detect, predict, and diagnose (Chilamkurthy et al., 2018; Shafaf and Malek, 2019) as well as for speech and image recognition (Peine et al., 2019; Rajpurkar et al., 2017).

Investments in AI applications for healthcare, particularly private investments, are increasing rapidly around the world (Zhang et al., 2022). However, AI applications in acute care remain in a comparatively early stage of development (Kirubarajan et al., 2020). That said, a rapid expansion in acute care is expected, given the recent advances in generative AI such as the GPT model and its integration into widely used software systems.

2.3. *The body of evidence on AI in acute care*

Research on the design, implementation, use, and effectiveness of AI applications has evolved in parallel to the proliferation of AI applications in acute care in the last five years (Zhang et al., 2021). The variety of such research and its broad distribution across academic disciplines, use cases, and dominant logics has thus far led to the lack of a coherent picture (Kirubarajan et al., 2020; Okada et al., 2021; Poncette et al., 2020). Literature reviews are critically important in this regard because they help synthesize the existing body of evidence and guide future research. Table 1 summarizes examples of literature reviews on AI in acute care, highlighting their research focus and purposes, along with their key findings.

These reviews show the diversity of AI applications in acute care and document the potential and versatility of AI applications in this field. That said, they widely diverge in terms of their research focus and purpose, evidence bases, and key findings. Some reviews focus on different classes of AI algorithms (e.g., ML, DL, supervised, or unsupervised learning) and their temporal evolution to delineate their potential in acute care (Chee et al., 2021; Kirubarajan et al., 2020). Other reviews focus on specific use cases of AI applications, including their use in prevention, diagnosis, decision-making, adverse drug events, or visual representation (Boonstra and Laven, 2022; Choudhury and Asan, 2020; Piliuk and Tomforde, 2023).

Despite these important integrative efforts, the research landscape of AI in acute care remains fragmented. As a result, a more comprehensive understanding of the current state of the art of AI in acute care is missing. This makes it difficult to systematically evaluate prior AI applications and design future ones. Particularly, prior reviews surprisingly ignore how AI applications interact with and create value for key stakeholders like clinical and non-clinical experts, patients, and their relatives. An institutional logic perspective helps explain this imbalance (Hansen and Baroody, 2020) Indeed, many of the reviews and the studies synthesize implicitly adopt a *professional* logic emphasizing quality of care or a *technical* logic focusing on algorithm and application design. However, a *business* logic focusing on efficiency as well as a *market* logic emphasizing patient choice and patient experience are vastly underrepresented in current literature on AI in acute care (see Table 1). This contradicts recurrent calls for more comprehensive evaluations of AI in healthcare with greater emphasis on the human element in AI implementation and use (e.g., Cresswell et al., 2023). It also disregards the longstanding political will to "*harness the information revolution and use it to benefit patients*" (The Prime Minister, Tony Blair, All Our Tomorrows Conference, Earls Court, London, 2 July 1998 as cited in Currie and Guah, 2007).

As we argue below, the theoretical lens of the SDL is well-suited to

Table 1
Overview of exemplary literature reviews on AI in acute care.

Research paper	Unit of analysis	Evidence base[a]	Review purpose	Review procedure	Review outcome	Logic
Aleksandra et al., 2024	Emergency care	$N = 51$	Overview of ML applications and its benefits	Clustering of AI applications: prehospital stage and triage, different types of diagnostic procedures	• AI applications mainly support doctors in diagnostics • AI results need to be verified by doctors	Professional logic, technology logic
Boonstra and Laven, 2022	Emergency care	$N = 34$	Overview of AI applications and impact on the work design	Clustering of AI applications: purpose of AI use, impact on work design	• Most of the AI applications support clinical decision-making and relieve overcrowding	Professional logic, business logic
Chee et al., 2021	Covid-19 disease in emergency care and intensive care unit	$N = 14$	Overview of AI applications for clinical management of Covid-19 patients	Comparison of review method, risk of biases, and AI algorithms	• Most of the studies developed prognostic or diagnostic AI predictive models • AI applications for Covid-19 are not ready for deployment	Technology logic
Choudhury and Asan, 2020	Patient safety	$N = 53$	Overview of AI applications to identify the health risks of patients	Clustering AI applications: clinical alarms, safety, and drug events, type of AI system	• AI applications are mainly based on decision tree models and support vector machine models	Technology logic, market logic
Kirubarajan et al., 2020	Emergency care	$N = 150$	Overview of AI applications	Comparison of review method, sample size, research location, type of AI algorithm	• Most studies are retrospective, followed by prospective controlled trials • Main purpose of AI application is to improve diagnosis	Professional logic, technology logic
Piliuk and Tomforde, 2023	Emergency care	$N = 116$	Overview of ML and DL application	Clustering AI applications: diagnostic and triage specific branches	• AI application studies remain isolated and lack higher generalizability	Professional logic, technology logic

[a] Final set of studies examined.

respond to these calls and rebalance, if not integrate, the coexisting institutional logics. Thus, SDL paints a more integrative, comprehensive, and human picture of AI design, use, and effectiveness in acute care.

3. Toward a service-dominant logic perspective on AI in acute care

3.1. SDL in acute care

Service-dominant logic (SDL) as a conceptual framework has influenced various fields, including service, marketing, innovation, and information systems research (Frow et al., 2016; Pinho et al., 2014). It is one of the most relevant service theories (Vargo and Lusch, 2017). It serves as a vehicle to find new value-creation opportunities, analyze existing actors' interactions in their ecosystems, and elicit missing resources (Callaway and Dobrzykowski, 2009). As a framework, SDL offers foundational premises that can deepen the understanding of value co-creation processes in healthcare. It asserts that value is co-created by multiple actors (e.g., medical staff and patients) through resource integration and service exchange (Frow et al., 2016). These actors thus play a key role in value creation (i.e., the medical treatment process). In today's multi-actor settings, actors exchange resources and capabilities, during which value-creation processes take place (Vargo and Lusch, 2017). These processes are coordinated by actor-generated institutions, including rules, norms, and beliefs (Vargo and Lusch, 2015). At a broad level, AI can facilitate and enhance resource and capability integration between actors, contributing to information availability, transparency, and dissemination (Zhang et al., 2020).

In healthcare, digital service transformation constitutes one of the great challenges. It is a process to relieve multiple actors, such as physicians, nurses, and patients, by transforming traditional, non-digital processes into more digitalized treatment and care service processes (Kraus et al., 2021). Researchers have found that one of the major barriers to digitizing processes in healthcare is the failure to involve actors in the process (e.g., Mayer and Strich, 2023; Stead, 2023). Another barrier is the complexity resulting from the involvement of diverse disciplines in the process (Hausberg et al., 2019). Using SDL helps connect disparate disciplinary domains so the complex service environment can be understood (Zhang et al., 2015). It underscores the collaborative nature of healthcare service provision. Integrating resources from various actors in the system is essential for co-creating value, especially for the patients (Zhang et al., 2015). After introducing AI applications to the transformation process in healthcare, AI enters the value-creating constellation as a new actor (Robinson et al., 2020). When seen through the lens of SDL, these AI applications can create new resources (knowledge and skills) and enhance existing capabilities (Akter et al., 2023).

3.2. Value co-creation in AI-augmented acute care

Service-dominant logic (SDL) emphasizes collaborative value co-creation among actors within healthcare systems by changing a transactional approach to a patient-centric one (e.g., Russo et al., 2019). In service marketing literature, *value* is defined as the benefit that results from co-creation by using a service, which is referred to as *value-in-use* or *value-in-context* (Hardyman et al., 2015). According to this logic, the different actors cannot deliver value. However, they can offer value propositions to another actor, where the interaction of these actors constitutes the actual value (Vargo and Lusch, 2011). This means that value is determined and assessed by the beneficiary, typically the customer (i.e. the patient), in a particular context (Pinho et al., 2014; Zhang et al., 2015). In the healthcare context, medical staff, including nurses, physicians, and patients dynamically co-create value throughout the treatment process. In the critical care sector, such as acute care, the extended environment of patients can play a significant role (McConnell and Moroney, 2015). Therefore, at times relatives might take an active service interaction role as well (Zotterman et al., 2018). Fig. 1 displays the underlying value co-creation process, focusing on the micro level interaction between patient or family members and medical staff. The distinction is made between different actors and interaction levels (e.g., micro and *meso* level). The various levels are nested and linked through value propositions offering access to additional resources, knowledge, and expertise (Chandler and Vargo, 2011; Frow et al., 2016).

The treatment process constitutes the exchange of service through knowledge and skills. In this process, the patient plays an active role (Sweeney et al., 2015). Customer value co-creation is the realization of benefits by integrating resources through activities and interaction between different actors in a service network. In this definition, *activities* describe behavioral performances (*doing*), whereas *interaction* constitutes actors' engagement with each other (McColl-Kennedy et al., 2012). Value co-creation can be achieved through different levels of activities. Those initiated by patients can range from simply providing health information to physicians up to complex activities such as co-learning during the treatment process through seeking and sharing feedback (e.g., communication of health status) (McColl-Kennedy et al., 2012).

In healthcare, optimizing the value creation potential for patients is a central goal (Lee, 2019; Porter, 2009); for example, through the treatment and recovery process that patients undergo with other actors (Osei-Frimpong et al., 2015). To increase value creation potential, hospitals seek to improve patients' outcomes, reduce their treatment costs, or excel at both (Porter, 2010; Zanetti and Taylor, 2016). To this end, new technologies such as AI can generally support humans (Jiang et al., 2017; Kokshagina, 2021; Supriya and Deepa, 2020). Broadly speaking, hospitals can use AI applications to augment human actors in accomplishing relevant tasks or to fully automate these tasks (Raisch and Krakowski, 2021). According to SDL, technology in general and AI in particular are dynamic operant resources that offer knowledge and skills that can facilitate value co-creation (Balta et al., 2021; Kaartemo and Helkkula, 2018; Jaakkola and Alexander, 2014). The integrative nature of SDL as well as its multi-actor foci serves as the ideal framework to synthesize prior research on AI applications in acute care.

3.3. Actors in acute care

Acute care is a complex service setting composed of multiple actors such as patients, physicians, and nurses. It is largely regulated by state health authorities and government agencies (Hirshon et al., 2013). At the macro level of its ecosystem, institutional logics regulate the provisions. At the operational level, the *meso* and micro levels play significant roles. At these levels, SDL draws attention to value co-creation and exchange processes between involved actors and their interactions (Breidbach et al., 2016; Chandler and Vargo, 2011). The micro level consists of key actors like different physicians, e.g., neurologists, anesthesiologists, and radiologists; but also family members, nurses, cleaning staff, and many more (Frow et al., 2016). On the micro level, actors are connected to different networks, such as families, companies, and other institutions (Chandler and Vargo, 2011). Thus, their roles and activities might differ depending on their relationship to other actors and the resource integration activity involved (Akaka et al., 2013; Chandler and Vargo, 2011). Each micro level interaction is nested and interconnected within a broader meso level (Chandler and Vargo, 2011). In the healthcare context, the meso level includes key actors like hospitals, clinics, and healthcare departments (Frow et al., 2016).

3.4. The patient journey in the acute care process

When seen through the eyes of the patient, the treatment process resembles a unique and often complex journey in which the patient interacts with diverse medical actors (Breidbach et al., 2016; Gualandi et al., 2019). Mapping this journey is vital to understand the different touchpoints across actors and along the treatment process with its key activities, interventions, and interactions of the treatment process to see

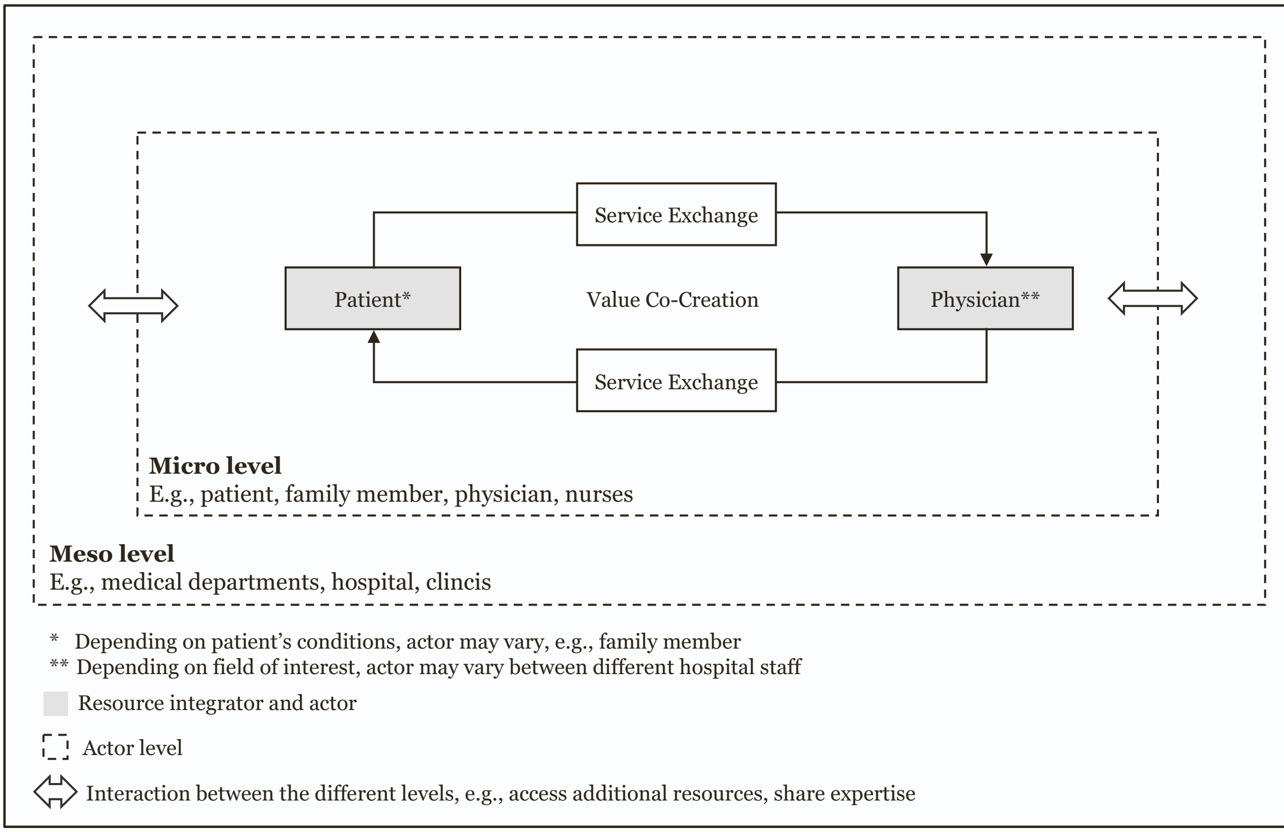

Fig. 1. Value Co-Creation Process in Healthcare.

from the patient's point of view what should be improved (Trebble et al., 2010). In hospitals, the patient journey serves as a cross-functional process tool to understand interactions between patients and providers and to map systems interactions between various touchpoints (Gualandi et al., 2019). It includes all relevant activities and steps of the value co-creation process (Zomerdijk and Voss, 2010). Fig. 2 illustrates the simplified process. In acute care, patient involvement is important given that a patient's life and quality of life are at stake. However, patient involvement can be challenging if a patient is affected by a severe condition (Breidbach et al., 2016).

The patient journey can be structured as five main process steps: 1) admission (including pre-admission, triage, and decision to admit); 2) diagnosis, 3) treatment, 4) discharge, and ending with 5) the post-treatment phase (Gualandi et al., 2019; Jiang et al., 2017; Lin et al., 2019). Depending on the progression of the medical condition, a patient might be re-admitted or admitted to another department in a possible sixth step (Mišić et al., 2020; Rojas et al., 2018). Applying AI could augment or automate relevant tasks in distinct phases of the patient journey (Hanson and Marshall, 2001; Kelly et al., 2019; Mathur and Burns, 2019).

4. Research methodology

4.1. Review approach

In the context of our study and given the focus of most existing studies within the field, we zoom into the micro and *meso* levels in healthcare. Taking a closer look at the end users offers the possibility to highlight the interdependencies and interactions between them (Chandler and Vargo, 2011; Frow et al., 2016). We adopt an SDL perspective, drawing on its key concepts like the patient journey and the patient perspective to assess the status quo on AI research in acute care.

We combined a systematic literature review with a conceptual

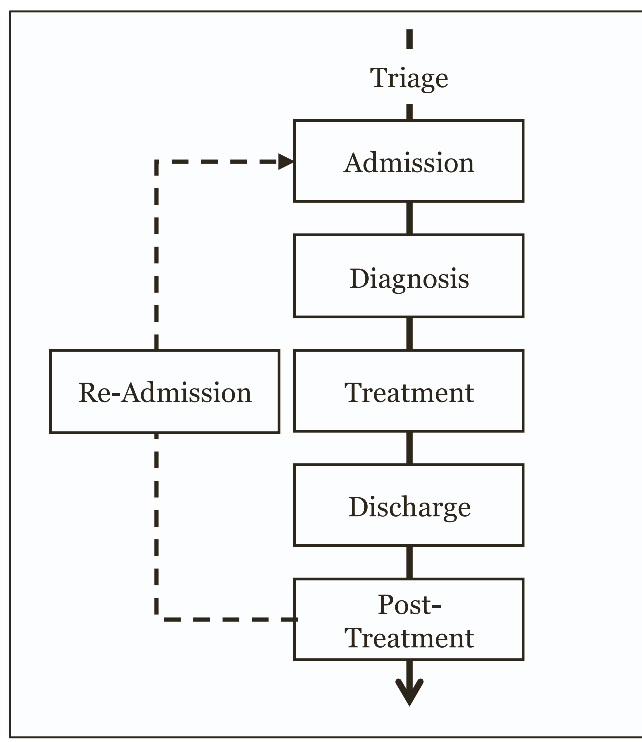

Fig. 2. A Patient Journey in Acute Care.

synthesis by using key SDL concepts to inform our coding scheme for the review. Performing a systematic literature review lets us identify current AI trends in acute care as documented in scholarly research. It also helps us to find areas in which future research is most needed. We conducted the initial review following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) method. This approach differentiates between four search phases: identification, screening, eligibility, and inclusion (Moher et al., 2009). During the eligibility phase, we added relevant key concepts from SDL to synthesize and discuss the body of AI research in acute care.

4.2. Sampling process

To prepare the initial search, we followed established search criteria for systematic literature reviews (e.g., Stead et al., 2022). To set up a keyword list, we first screened keyword selections in existing reviews of AI research and acute care. We considered "artificial intelligence, "deep learning," and "machine learning" to be the most frequently used search terms (Borges et al., 2021; Burlacu et al., 2020; Kirubarajan et al., 2020; Wingfield et al., 2020). To generate a comprehensive data set of AI use cases, we added a set of AI sub-fields and ML methods to the search string. We included additional search terms including "neural network," "supervised learning," "unsupervised learning," and "reinforcement learning." We searched for research papers focusing on the acute care context. Therefore, we included the search terms "acute care," "critical care," "intensive care," "emergency room," "emergency department," "trauma care," and "trauma center."

We conducted an open search to identify relevant research available on the *Web of Science platform*. In the next step, we defined inclusion and exclusion criteria to reach our final set of publications. See Fig. 3 for the underlying research and sample selection process.

We focused our analysis on journal articles in English that show a clear connection to AI applications in the acute care domain. Given the recent increase in AI research in acute care (Aleksandra et al., 2024; Zhang et al., 2021), we included journal articles published between 2018 and 2022. We then reviewed titles, abstracts, and keywords relevant to acute care. We included those papers that focused on AI and particular use cases. For example, we reviewed a paper dealing with an AI application designed to predict hospital admissions (Hong et al., 2018). We explicitly excluded reviews and summary reports. Additionally, we excluded research papers that did not focus on both acute care and AI (e.g., robotic or other contexts). After this initial coding phase, our data set contained 618 research papers (see Fig. 3). To ensure accuracy and completeness, we performed an independent double-blind coding process. In instances of deviations, we undertook additional iterations and discussions to generate a consistent and independent dataset. During the full-text screening, we excluded eight additional research papers because of missing acute care focus or limited access. Thus, our final data set consists of 610 research papers.

4.3. An SDL lens on AI research

To generate meaningful insights and provide theory-informed guidance, we adopted an SDL perspective on AI research in acute care. For the systematic coding of all research papers, we used key SDL concepts and represented them in a matrix. The framework consists of four dimensions: (1) the actors involved at the micro level, (2) the actors involved at the *meso* level, (3) the activities augmented or enabled by AI, and (4) the steps of the patient journey.

Specifically, we analyzed different actors who use AI and benefit from it on the micro and *meso* levels (Chandler and Vargo, 2011; Frow et al., 2016). Technology in the form of AI is defined here as an operant resource (a form of useful knowledge) that can be individually integrated for value co-creation (Vargo and Lusch, 2015). As such, SDL addresses service activities and processes of resource integration (Vargo and Lusch, 2015). Thus, we also assessed relevant service activities (e.g., prediction, identification, and detection) that AI enables. Next, we

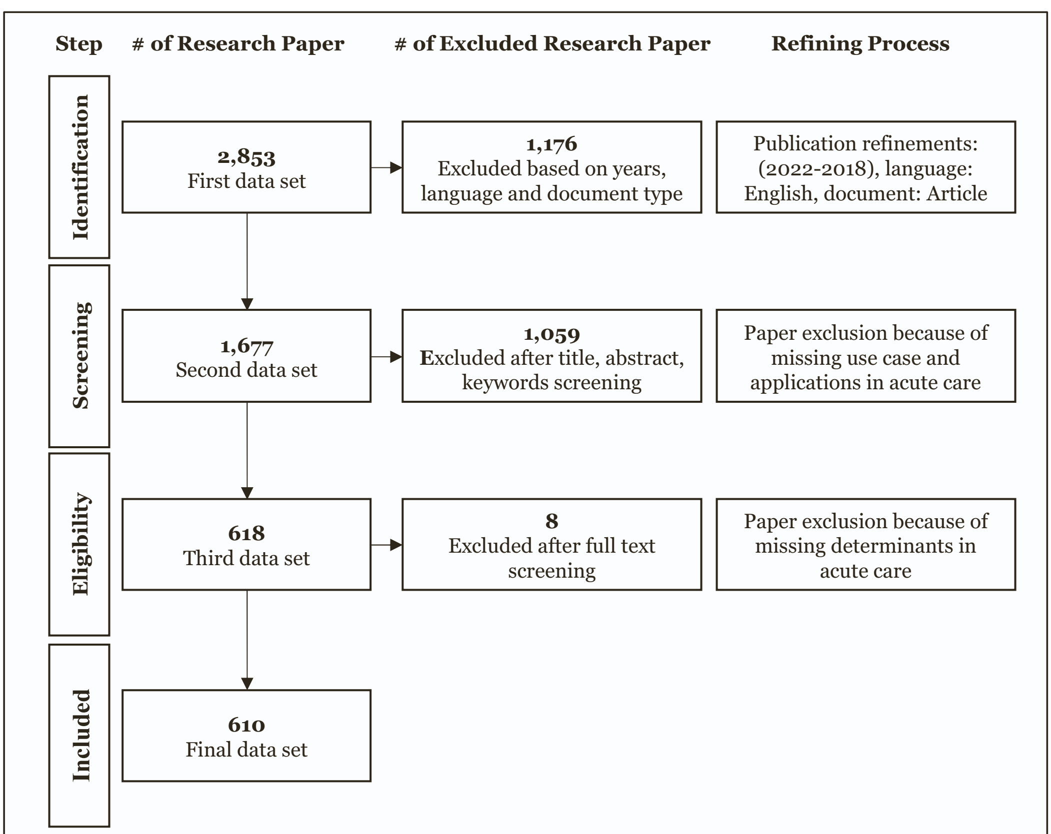

Fig. 3. Literature Review and Exclusion Process.

mapped these three dimensions onto patient journey steps to create a matrix to represent the results. The patient journey allows us to identify where AI touch points occur and draw attention to its corresponding users and beneficiaries (McCarthy et al., 2016).

5. Key findings from the literature on AI applications in acute care

Our final data set consists of 610 research papers focusing on AI applications in acute care. In line with existing AI research in acute care, most AI research in acute care originates from China and the US (Cheng et al., 2023). Meeting our expectations, research on AI applications in acute care is gaining attention. The COVID-19 pandemic ignited a wave of R&D for technology advancements (e.g., GPT models) and led to the need for research on assisting AI applications in acute care (Aleksandra et al., 2024; Chee et al., 2021. Our data set shows that AI research and development is four times higher in 2021 (e.g., 234 research papers) compared to 2018 (e.g., 55 research papers). However, most of the studies focus on retrospectives, for example, by accessing a large database (e.g., the MIMIC clinical database). This was followed by prospective studies to develop and train AI applications (Johnson et al., 2016) instead of performing actual clinical trials and conducting actual field tests (see Table 4). Applying a user-centric approach, we coded each paper along the four SDL dimensions outlined above. Thereby, we could make multiple allocations because some developed AI systems perform multiple activities (Dervishi, 2020; Heili-Frades et al., 2020). Table 2 through Table 6 summarize the corresponding results of our coding. The tables provide absolute values and percentage (rounded) values for each SDL concept. If we could not map a paper to a specific patient journey step, we added a step named “Other”. The papers allocated to “Other” focus on inventory management for consumables in hospitals, or patient screening for clinical trials (Ni et al., 2019; Peine et al., 2019; Zampieri et al., 2019).

5.1. Micro-level insights (key insight 1)

We first focus on the micro level perspective. Here, extant AI research has dealt with dyadic interactions between AI and intended end users. A majority (96.87 %) of the research papers examine AI applications geared toward hospital staff as intended end users and beneficiaries. The papers mainly focus on the treatment step - the third step of the patient journey (see Table 2). The hospital staff includes relevant actors, such as hospital administrators (responsible for bed and capacity management), nurses (responsible for triage decisions and monitoring), and physicians. Beyond that, we identified emergency dispatchers as additional end users. Surprisingly, the patient as an end user only plays a peripheral role in extant AI research. In fact, only three research papers study AI applications intended for direct patient interaction. The authors of these papers have developed ML systems to predict accurate waiting-times for patients in the emergency room (Kuo et al., 2020; Pak et al., 2021; Walker et al., 2022).

5.2. Meso-level insights (key insights 2 & 3)

At the meso level, AI research can be found across various acute care departments. The different departments specialize in providing care tailored to different medical conditions and patient needs. For example, medical staff in the intensive care unit deliver treatment and implement life-sustaining interventions. Medical staff in the emergency department promptly manage acute medical conditions and injuries (Hirshon et al., 2013). The trauma center specializes in patients with severe and multiple injuries (Tjardes et al., 2023). These *meso* level insights are essential to generate a comprehensive understanding of existing AI and to identify research opportunities. Table 3 summarizes the results. The coding reveals that AI research is mainly conducted in the emergency room and the intensive care unit. A large portion (87.36 %) of the research papers study AI applications to augment tasks in the first three patient journey steps of admission, diagnosis, and treatment. In the emergency room, for example, AI research has focused on predicting patient admission to the acute care department, as well as patient pathways, complications, and mortality (Ang et al., 2022; Hwang and Lee, 2022; Okada et al., 2021). In contrast, AI research for trauma care is scarce. Only 2.7 % of the research papers study AI applications for this area (see Table 3). This lack could be attributed to the complex and high-stakes working environment which restricts data collection (Tjardes et al., 2023; Tsiklidis et al., 2020).

In these departments, AI is suggested to improve tasks and activities supporting the patient journey steps. Next, we examine the research methodology of the empirical papers to learn more about the use of AI in acute care.

Our analysis shows that 96.22 % of the research papers focus on AI system development and proofs-of-concept, as opposed to performing field testing in actual clinical environments. Only 23 research studies employed and tested AI applications in clinical field settings. Table 4 summarizes these research papers. It shows the corresponding department (at the meso level), the patient journey step, and actual AI activity. Most of the studies used AI applications mainly to augment medical tasks and processes (e.g., Rosenthal et al., 2019; Qian et al., 2021). Only a few research papers focused on task automation. For example, in one research paper, the authors developed and tested a contactless visual recognition system to track medical consumable materials (masks, hand disinfection bottles, bandages) in an intensive care unit by using a DL approach with convolutional neural networks (Peine et al., 2019). This system was tested in a real intensive care unit environment and

Table 2
Overview of research on AI applications in acute care at the micro level.

Focal beneficiary	Patient journey step							Total
	Admission	Diagnosis	Treatment	Discharge	Post-treatment	*Re*-admission	Other	
Emergency dispatcher	**2** (0.3 %)	**0**	**1** (0.2 %)	**0**	**0**	**0**	**2** (0.3 %)	**5** (0.8 %)
Hospital administrator	**24** (3.7 %)	**0**	**1** (0.2 %)	**1** (0.2 %)	**0**	**2** (0.3 %)	**9** (1.4 %)	**37** (5.8 %)
N.A.	**1** (0.2 %)	**0**	**7** (1.1 %)	**0**	**0**	**0**	**9** (1.4 %)	**17** (2.7 %)
Nurse	**7** (1.1 %)	**5** (0.8 %)	**28** (4.4 %)	**0**	**0**	**0**	**0**	**40** (6.2 %)
Patient	**2** (0.3 %)	**0**	**1** (0.2 %)	**0**	**0**	**0**	**0**	**3** (0.5 %)
Physician	**76** (11.9 %)	**105** (16.4 %)	**300** (46.8 %)	**27** (4.2 %)	**7** (1.1 %)	**21** (3.3 %)	**3** (0.5 %)	**539** (84 %)
Total	**112** (17.5 %)	**110** (17.2 %)	**338** (52.7 %)	**28** (4.4 %)	**7** (1.1 %)	**23** (3.6 %)	**23** (3.6 %)	

Note: The final data set consists of N = 610; the percentages indicate the share of papers with the research focus among all papers reviewed.

Table 3
Overview of Research on AI Applications in Acute Care at the Meso Level.

Focal Department	Patient Journey Step							Total
	Admission	Diagnosis	Treatment	Discharge	Post-Treatment	*Re*-Admission	Other	
Acute Care in General	**2** (0.3 %)	**2** (0.3 %)	**5** (0.8 %)	**0**	**1** (0.2 %)	**2** (0.3 %)	**1** (0.2 %)	**13** (2 %)
Emergency Department	**64** (10 %)	**51** (8 %)	**80** (12.5 %)	**16** (2.5 %)	**4** (0.6 %)	**12** (1.9 %)	**14** (2.2 %)	**241** (37.6 %)
Intensive Care Unit	**43** (6.7 %)	**57** (8.9 %)	**241** (37.6 %)	**11** (1.7 %)	**1** (0.2 %)	**9** (1.4 %)	**8** (1.2 %)	**370** (57.7 %)
Trauma Center	**3** (0.5 %)	**0**	**12** (1.9 %)	**1** (0.2 %)	**1** (0.2 %)	**0**	**0**	**17** (2.7 %)
Total	**112** (17.5 %)	**110** (17.2 %)	**338** (52.7 %)	**28** (4.4 %)	**7** (1.1 %)	**23** (3.6 %)	**23** (3.6 %)	

Note: The data set consists of N = 610; the percentages indicate the share of papers with the research focus among all papers reviewed.

Table 4
AI research with clinical trials in acute care.

Research paper	Meso level	Patient journey step	Activity
Caparros-Gonzalez et al., 2018	Intensive care unit	Treatment	Classification of treatment procedure
Carlile et al., 2020	Emergency department	Diagnosis	Identification of disease
Dadon et al., 2022	Emergency department	Diagnosis	Identification of fractures
Földesy et al., 2020	Intensive care unit	Treatment	Identification of health parameters
Ghodratigohar et al., 2019	Intensive care unit	Treatment	Identification of health parameters
Heili-Frades et al., 2020	Intensive care unit	Treatment	Identification and classification of mortality predictors
Kadri et al., 2022	Emergency department	Discharge	Prediction of length of stay
Keim-Malpass et al., 2021	Intensive care unit	Admission / treatment	Prediction of pathway
Kim et al., 2021	Emergency department	Diagnosis	Identification of injury
Liu et al., 2022	Emergency department	Admission	Identification of patient capacity
Lyra et al., 2022	Intensive care unit	Treatment	Detection of health parameters
Magunia et al., 2021	Intensive care unit	Treatment	Prediction of pathway
Ni et al., 2019	Emergency department	Other	Identification of patients for clinical trials
Oernek et al., 2020	Intensive care unit	Diagnosis	Classification of subgroups
Peine et al., 2019	Intensive care unit	Other	Classification of consumable materials
Puttinaovarat et al., 2021	Emergency department	Treatment	Classification of subgroups
Qian et al., 2021)	Intensive care unit	Admission	Prediction of patient capacity
Rosenthal et al., 2019	Emergency department	Treatment	Data structuring
Severini et al., 2019	Intensive care unit	Treatment	Classification of cry
Villarroel et al., 2019	Intensive care unit	Treatment	Prediction of health parameters
White et al., 2021	Emergency department	Treatment	Detection of disease
Yousefi et al., 2019	Emergency department	Admission	Prediction of patient capacity
Yuan et al., 2020	Intensive care unit	Diagnosis	Early sepsis diagnosis

performed well according to the authors. Using such a system can enable medical staff to accurately and automatically manage medication (Peine et al., 2019). Nonetheless, Peine et al. (2019) highlighted limitations in the system's ability to identify consumables when covered. Further development and refinement of the system are needed to optimize its performance (Peine et al., 2019). This example also shows the limitations of AI applications and raises questions about responsibility in such situations (Cresswell et al., 2023; Kelly et al., 2019).

5.3. Activity-level insights

In the next step, we analyzed extant research on AI in acute care with a focus on the specific activity performed or supported by the corresponding AI application. Table 5 provides an overview.

Our findings show that current researchers have studied AI's potential to support relevant activities ranging from prediction (e.g., patient capacity or length of stay) and identification (e.g., health parameter or disease) to classification (e.g., subgroups or treatment procedure) and research purposes (e.g., potential for new AI applications) (see Table 3). A robust 75.32 % of all papers in our sample focus on prediction and identification during the first three patient journey steps. For example, one research team developed and tested an artificial neural network to predict trauma admission volume and acuity by combining admission and weather data from several US trauma centers (Stonko et al., 2018). Such AI applications can help with planning and allocating hospital resources (Stonko et al., 2018).

Furthermore, we find important differences between the AI activities of different beneficiaries. Table 6 shows a breakdown of AI activities and outcomes by beneficiary. We identify AI solutions that aim to manage occupancy capacity, simplify processes, and support hospital staff. Thus, these solutions improve treatment quality and accuracy as well as patient value (Topaz et al., 2020; Tsiklidis et al., 2020). For example, one empirical study investigates the use of DL methods (recurrent neural networks) to predict severe clinical outcomes in real-time, such as mortality, renal failure requiring additional therapy, or postoperative hemorrhage (Meyer et al., 2018). The DL method proposed in this study makes accurate predictions based solely on routinely collected clinical data. Using the proposed DL method can help medical staff focus on high-risk patients (Meyer et al., 2018).

6. Discussion

In our systematic literature review, we map published AI research in acute care using four key concepts from SDL. This contributes to a comprehensive understanding of the extant body of evidence in the field (see Table 2 to Table 6). With SDL, we can integrate the three competing institutional logics in healthcare – professional, business, and market – and generate a comprehensive, balanced understanding of prior AI research and future research priorities in acute care. We (1) identified intended users of AI on the micro and *meso* levels, (2) analyzed activities supported by AI, and (3) connected these insights to AI-supported patient journey steps. The results of using AI to support and improve the

Table 5
Overview of research on AI applications in acute care at the activity-level.

Focal Activity	Patient Journey Step							Total
	Admission	Diagnosis	Treatment	Discharge	Post-Treatment	Re-Admission	Other	
Classification	**4** (0.6 %)	**19** (2.7 %)	**24** (3.4 %)	**1** (0.1 %)	**0**	**0**	**2** (0.3 %)	**50** (7.1 %)
Detection	**0**	**14** (2 %)	**18** (2.6 %)	**0**	**0**	**0**	**0**	**32** (4.5 %)
Identification	**19** (2.7 %)	**34** (4.8 %)	**83** (11.8 %)	**3** (0.4 %)	**3** (0.4 %)	**9** (1.3 %)	**3** (0.4 %)	**154** (21.8 %)
Prediction	**101** (14.3 %)	**55** (7.8 %)	**239** (33.9 %)	**25** (3.5 %)	**5** (0.7 %)	**18** (2.6 %)	**9** (1.3 %)	**452** (64.1 %)
Research	**1** (0.1 %)	**0**	**7** (1 %)	**0**	**0**	**0**	**9** (1.3 %)	**17** (2.4 %)
Total	**125** (17.7 %)	**122** (17.3 %)	**371** (52.6 %)	**29** (4.1 %)	**8** (1.1 %)	**27** (3.8 %)	**23** (3.3 %)	

Note: The final data set consists of N = 610. The percentages show the share of papers with the research focus among all papers reviewed.

Table 6
Overview of AI activities and outcomes by focal beneficiary.

Focal beneficiary	AI activities	Total count	Example references
Emergency dispatcher	Prediction of ambulance resources	5	Li et al., 2022
	Prediction of complications		Tollinton et al., 2020
Hospital administrator	Classification of medical consumables	37	Peine et al., 2019
	Detection of health parameters		Lyra et al., 2022
	Identification of human resources		Yousefi and Yousefi, 2019
	Prediction of patient capacity		Peng et al., 2020
	Prediction of re-admission		Sarasa Cabezuelo, 2020
Nurse	Detection of health parameters	40	Lyra et al., 2022
	Identification of false alarms		Zhou et al., 2022
	Prediction of triage level		Choi et al., 2019
Patient	Prediction of patients' waiting time	30	Pak et al., 2021
Physician	Diagnosis of disease	539	Yuan et al., 2020
	Identification of treatment procedure		Qiu et al., 2022
	Prediction of disease pathway		Schwab et al., 2020
	Prediction of disposition		Sterling et al., 2019
	Prediction of mortality		Okada et al., 2021

Note: The final data set consists of $N = 610$.

treatment process appear promising. In our analysis, we show the status quo of AI research in acute care and identify example studies in this space. Next, we propose a research agenda for future AI research in acute care.

6.1. Toward a research agenda

We derive three key insights and propose a future research agenda for acute care AI applications. For each insight, we develop a corresponding research priority. We propose promising research questions and suggest supporting frameworks, tools, and references for future researchers. Table 7 provides an overview.

6.1.1. Researching the triadic interaction between different beneficiaries and AI applications

We find that much prior research on AI in acute care focuses on hospital staff (e.g., physicians, hospital administrators, and nurses) as actors, with the goal of improving patients' recovery and accelerating treatment processes (Guntuku et al., 2020; Meyer et al., 2018; Schwab et al., 2020). Our results show that the patient only plays a peripheral role. Maximizing value for the patient, however, requires considering their recovery and experiences during treatment (Osei-Frimpong et al., 2015). According to SDL, the customer (i.e., the patient) plays a central role in the value co-creation process (Vargo and Lusch, 2017). Therefore, it is essential to broaden the theoretical lens for AI research and adopt a multi-actor perspective to assess the interaction between hospital staff, patients, and the AI application. In line with SDL, especially in the role of the new "actor," AI can profoundly affect traditional patient-physician interactions. Therefore, a narrow focus on individual actors will likely contribute to an incomplete picture. We argue for a more comprehensive perspective to tailor AI applications to the multifaceted needs of all key actors involved in the treatment process. We recommend emphasizing the triangular relationship between AI applications, clinical staff, and patients.

Importantly, mapping existing processes and determining where the new actor of AI intervenes with existing processes should be the first step. We suggest that future researchers should use tools such as service blueprinting (e.g., Bitner et al., 2008; Patrício et al., 2011) and patient journey mapping (Borycki et al., 2020) to assess the treatment process and interventions from a multi-actor perspective. A blueprint depicts the front and back stages of a treatment process. Mapping the process generates a deeper understanding of all activities performed by the different actors (e.g., hospital staff and patients). The corresponding back-office support of IT, and the AI algorithms that the department uses, can be visualized and analyzed at each touchpoint. Capturing and analyzing the patient journey helps map the treatment process from a patient's perspective. It also enables the detection of important digital interfaces that can facilitate or impede interactions between actors (Parush et al., 2021; Trebble et al., 2010; Simonse et al., 2019). Simonse et al. (2019), for example, used the patient journey to assess several relevant factors to improve processes, including the location where care takes place, the individual step in the care process, and the interaction of specific actors. Borycki et al. (2020) took this approach further to identify existing and missing technology resources in healthcare processes. Using the patient journey as a tool can help integrate appropriate service technology systems in healthcare (Simonse et al., 2019) and more accurately show where AI applications can outperform existing systems (Parush et al., 2021).

6.1.2. Examining AI applications to support underexplored patient journey steps

We found extant research to focus on AI applications to improve the admission, diagnosis, and treatment steps of the patient journey in acute care (e.g., Jiang et al., 2017; Meyer et al., 2018; Pak et al., 2021). Following the patient journey at the most aggregate level, there are at

Table 7
Key insights and future research priorities.

Key Insights	Description	Future Research Priorities	Future Research Questions	Supporting Frameworks	Exemplary References
Key Insight 1	97 % of research papers focus on the dyadic interaction between hospital staff and AI system	Researching the triadic interaction between different beneficiaries and AI applications	• How does the new actor (AI) change existing interactions and relationships along the patient journey? • To what extent is the AI co-creating or deconstructing value for the different actors (e.g., medical staff, patient)?	• Service Blueprint • Patient journey	Bitner et al., 2008; Borycki et al., 2020; Parush et al., 2021; Simonse et al., 2019
Key Insight 2	87 % of research papers study AI solutions for the first three patient journey steps	Examining AI applications to support underexplored patient journey steps, namely discharge, post-treatment, and re-admission	• How can AI applications be leveraged to augment the patient journey in a meaningful way? • Where should AI take an automating vs. augmenting role in the patient treatment process?	• Co-creation • Double diamond model of design thinking	Banbury et al., 2021; Park and Lee, 2021; Zhang et al., 2019
Key Insight 3	96 % of research papers focus on AI system development and proof-of-concepts studies	Testing AI applications in realistic clinical settings with involvement of multiple stakeholders	• What are the long-term effects of implementing AI applications in the treatment process on patient-staff interactions? • What factors drive the adoption or avoidance of AI applications from a clinical staff and patient perspective?	• Experimental design • Translational evaluation of healthcare AI model	Montgomery, 2017; Reddy et al., 2021

least three more process steps, including discharge, post-treatment, and possible re-admission. These have been underexplored by prior AI researchers (Fig. 2). However, to achieve long-term improvements using AI during the treatment process, one must draw attention to the entire patient journey, considering both digital and physical interactions at all steps. Assumptions about the patient journey and how to optimize single touchpoints require a broader and deeper analysis of the entire journey (e.g., Stead et al., 2023). From the perspective of both the organization and the patient, this is especially important given the interconnection of patient journey steps at the micro and *meso* levels. For example, if patients are wrongly admitted to hospital departments, or there is a delay in admission, it can profoundly affect further treatment process steps or cause complications and negative long-term effects (Guntuku et al., 2020; Okada et al., 2021; Pan et al., 2020).

To develop fully integrated AI systems, a more user-centered and co-creative approach is needed. Optimizing the interaction points between actors is instrumental in developing new business opportunities (Vargo and Lusch, 2004). We suggest employing the so-called double diamond model. This model encompasses four phases: discovery, defining, development, and delivery. The approach is based on the divergence-convergence model introduced by Banathy (1996). The first diamond focuses on the phases of discovering and defining the current situation and key problems that need to be addressed. This phase involves considering a broad spectrum of ideas. It is followed by a deeper thinking perspective. In the second diamond, the focus shifts to developing and delivering the actual solution (Park and Lee, 2021; Design Council, 2019). In the two diamonds, a mutual exchange takes place between exploring (divergent thinking) and taking action (convergent thinking). The diamonds can be used iteratively, where each identified problem listed on the blueprint can be subject to a distinct iteration (Design Council, 2019; Banathy, 1996). This framework is not entirely new to healthcare. It has shown its potential to co-design processes and develop new (technology) solutions (see e.g., Banbury et al., 2021; Park and Lee, 2021; Zhang et al., 2019).

The results of our analysis show that the last three patient journey steps in particular require attention to additional AI research. By applying the double diamond model, researchers can perform targeted problem exploration and definition in these patient journey steps. This is followed by the development of an AI solution, and finally by the testing phase (Design Council, 2019). In this way, the potential for value co-creation instead of risking value co-destruction can be realized. Overcoming detected issues during the patient-treatment process may result in better care and hospital performance (Stead et al., 2023). This in turn could stimulate a more balanced approach, integrating all three logics.

6.1.3. *Testing AI applications in realistic clinical settings*

According to SDL, the purpose of organizations is to create the highest value for the customer, meaning the patient (Lee, 2019; Porter, 2009). To provide robust clinical evidence for the value of the patient interacting with AI, applications must be tested and implemented within realistic care settings. These tests could be simulated or real clinical environments involving all relevant actors. This approach enables the development of targeted AI solutions adapted for clinical needs (Kueper et al., 2020; Shimabukuro et al., 2017). However, extant research focuses on system development instead of implementing and testing suitable systems in real-life clinical environments (see Table 3). In line with previous research (Hanson and Marshall, 2001; Kirubarajan et al., 2020), our analysis suggests that AI research in acute care is at an early stage. Throughout the AI development process, AI systems should be tested in multistage experiments ranging from laboratory and simulated clinical studies to real clinical settings (Peine et al., 2019; Severini et al., 2019; Thakur and Lahiry, 2021). Experimental designs can assist in this process and drive innovation. Early application of experimental designs can reduce slack in innovation processes, help assess technology parameters, and show system performance requirements. This approach can ensure a smoother implementation to practice (Montgomery, 2017). As previous researchers have shown, requirements in clinical settings could change depending on data acquisition, data availability, and preferences of clinical professionals (Okada et al., 2021; Zhang et al., 2021).

To enhance AI development and increase its adoption, Reddy et al. (2021) suggest a translational evaluation of the healthcare AI model to assess real-world technology systems in various phases. The model distinguishes between the development, deployment, and discernment phases. It defines assessment categories for each phase (Reddy et al., 2021) and can provide a fitting framework for future researchers to build upon.

6.2. Theoretical implications

Our literature review contributes to the emerging AI research in two ways. First, we used a systematic approach to synthesize AI research in acute care. Previous literature reviews focused on specific use cases and healthcare areas to scope and structure their reviews (Boonstra and Laven, 2022; Chee et al., 2021; Kueper et al., 2020). We used SDL, which emerged as a theoretical lens from service science, as our structuring mechanism. Using SDL offers opportunities to bridge the three institutional logics (professional, business, and market logic). In this way, researchers can gain a more holistic understanding of the body of literature on AI applications in healthcare. As we illustrate, SDL can advance the development and design of AI applications in acute care and help balance the body of empirical research in this space. With this approach, we answer research calls that suggest exploring patient engagement and value co-creation within health service encounters (Cresswell et al., 2023; Russo et al., 2019). Emerging literature in services marketing and public management suggests SDL is a suitable means of exploring value co-creation in healthcare. This lens draws attention to important dimensions. These consist of intended end users at the micro and *meso* levels, corresponding activities performed by AI, and the specific steps of the patient journey. Based on our results, we derived three future research priorities, proposed future research questions, and provided concrete frameworks and tools to support future research. Our study also contributes to calls for more research to capture the status quo of AI research in the critical area of acute care (Kirubarajan et al., 2020).

Second, by employing SDL as a conceptual framework in our systematic literature review, we can identify important blind spots in our current understanding of AI use in acute care. Using relevant SDL concepts as a coding scheme, we found three main research gaps. These research gaps were in researching the triadic interaction between different beneficiaries and AI applications, examining AI applications to support underexplored patient journey steps, and testing AI applications in realistic clinical settings. We provide appropriate methods from the service discipline to close these gaps. By mapping AI research across the micro, meso, and macro levels, we can link intended end-users, AI activity, and the corresponding patient journey step, showing their relationships. These findings can guide future researchers to develop, analyze, and test new AI applications in acute care.

6.3. Practical implications

In addition to our theoretical contributions, our work illustrates practical implications. We show that SDL is a suitable theoretical lens to view the different institutional logics. Being able to bridge the gap between these logics allows healthcare practitioners to improve treatment processes. Our insights are especially relevant for managers, decision-makers, frontline staff using the AI system, and back-office IT and system developers.

Healthcare managers and decision-makers can use the SDL lens and the findings of this study to balance the different institutional logics in healthcare and improve treatment processes We present SDL as a suitable framework for assessing existing healthcare processes, identifying needs, and discovering ways to advance these processes through tailored AI solutions. Using SDL can help managers implement strategies to guide hospital staff to apply supporting AI applications in a systematic and user-centric way. Evaluating AI application usage from a multi-actor perspective can guide managers and decision-makers when developing, testing, and implementing novel AI solutions. For example, investigating the interaction with AI applications along the patient journey lets managers and decision-makers allocate resources and the infrastructure requirements to smoothly implement AI solutions. Based on the micro and meso level perspective, practitioners can learn by testing AI in use. Managers and decision-makers can build upon the insights derived from this study to develop targeted education and training programs for the intended end users using the tools we list and considering specific requirements along the patient journey. Applying a user-centric approach might help to overcome existing barriers to future AI implementation and increase end users' acceptance and adoption of AI (He et al., 2019; Kelly et al., 2019; Yadav et al., 2022).

In portraying the status quo of AI research, we hope we can raise the understanding of the importance of studying the different patient journey steps. We also aim to show the urgency of and benefit for healthcare organizations to collaborate and open doors for future AI research endeavors. We present a detailed representation of current AI research in this study. As such, it can shift attention to knowledge gaps and help actors understand the untapped potential of AI applications in their domain. This can lead to system developers using our findings to develop needed AI applications relevant to each step on the patient journey, taking into account all actors involved. Our paper shows the gap between the development of prototypes and the actual usage of certified AI applications in daily practice, reflected in scholarly research. Therefore, we encourage system developers, researchers, and practitioners to join forces. Together they can counteract these shortcomings, particularly those involving anticipated end users in the early stages (Singh et al., 2024). Assistive multi-actor techniques for the research, development, and design stage include tools we have discussed, such as service blueprints, patient journeys, or the double diamond model (Borycki et al., 2020; Banbury et al., 2021).

6.4. Limitations and future research

Inevitably, our study has some limitations that future researchers should address. First, we restricted our systematic search to the *Web of Science* platform, which includes only journal articles. To expand our findings, future researchers can extend the article pool by drawing on books and conference papers covering AI applications in healthcare. Because AI research in acute care is in its infancy, analyzing early work such as conference papers could provide additional insights. Moreover, we organized our review around four key SDL concepts: actors at the micro and meso levels, corresponding AI activities, and the patient journey. We acknowledge that issues beyond the scope of our review have value for AI research in healthcare. Future researchers could, for example, analyze value co-creation and co-destruction mechanisms of already established AI systems. We also encourage future researchers to look beyond the micro and meso levels. We encourage them to examine the macro level of interacting organizations (e.g., hospitals, insurance, pharma) in the broader institutional field of healthcare. Evaluating these aspects can benefit both research and practice. It could strengthen tailored AI system development and increase end users' ability to understand and interact with the system. As AI applications are integrated into various fields, researchers must analyze potential errors and limitations of AI applications. Critical reflection on possible responsibility shifts between humans and AI is also needed in future research.

Clearly, our study is the first effort to assess AI research using the SDL framework as a conceptual lens. We chose acute care as a challenging service setting well-suited to highlight the complexity of multi-actor involvement. To establish a universal framework to synthesize AI research in service settings, exploring other contexts in healthcare and beyond is required.

7. Conclusion

In complex and dynamic environments such as healthcare, finding the right balance between different logics like professional, business, and market logic can be challenging. Providing the best possible treatment to patients should always incorporate high quality. However, it also must be efficient from an employee and organizational perspective. The use of AI applications will help balance these requirements by assisting and improving acute care. However, the development of AI and published research in that context is fragmented (Aleksandra et al., 2024; Chee et al., 2021; Kirubarajan et al., 2020). Against this backdrop, we aim to systematically analyze AI research in acute care from the perspective of SDL. Using SDL opens pathways to apply a more user-centric perspective on AI applications and bridge competing institutional logics. Our study showcases the potential of SDL in this context and provides a conceptual synthesis of the extant body of evidence. We have identified the end users of AI systems on the micro and meso levels and clustered relevant AI activities along the patient treatment journey. Our study demonstrates that SDL can be a useful lens to systematically analyze and advance AI research. In summary, we mapped the current state of AI research, identified research gaps, defined important research priorities, and suggested research questions and tools to close knowledge gaps. Our insights can guide future researchers on AI applications in acute care, which arguably are poised to enter their most exciting developmental phase.

CRediT authorship contribution statement

Lea Mareen Meyer: Writing – review & editing, Writing – original draft, Visualization, Project administration, Methodology, Investigation, Formal analysis, Conceptualization. **Susan Stead:** Writing – review & editing, Writing – original draft, Supervision, Methodology, Conceptualization. **Torsten Oliver Salge:** Writing – review & editing, Writing – original draft, Supervision, Resources, Funding acquisition, Conceptualization. **David Antons:** Writing – review & editing, Resources, Funding acquisition.

Data availability

Data will be made available on request.

Acknowledgements

The research project was funded by the German Federal Ministry of Health.

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Lea Mareen Meyer is a PhD student at the Institute for Technology and Innovation Management at RWTH Aachen University. She studied business administration at RWTH Aachen University, Germany and IESEG School of Management in Paris, France. As part of her research program, she collaborated with healthcare organization to support digital transformation such as AI technologies in the healthcare sector. Beyond that she is a member of the healthcare innovation lab, which aims to accelerate the digitalization process in healthcare and interconnect technology, healthcare, and research at the same time.

Susan Stead is Assistant Professor and Director of the Healthcare Innovation Lab and Digital Responsibility Lab at the Institute for Technology and Innovation Management, TIME Research Area at RWTH Aachen University, Germany. She received her PhD from Maastricht University, the Netherlands. During her PhD trajectory, she was an associate partner PhD in the European Service Design for Innovation (SDIN) Network for Early-Stage Researchers (ESRs). Her research interests include service science, multisensory customer experience, service innovation, and digital transformation in healthcare settings. Her early work appeared in the Journal of Service Research, Journal of Service Management, Journal of Services Marketing, ICIS Proceeding, and Journal of Hospital Infections.

Torsten Oliver Salge is a professor and co-director of the Institute for Technology and Innovation Management (TIM) in the TIME Research Area at RWTH Aachen University, Germany. He received his Ph.D. from the University of Cambridge and has held (visiting) appointments at universities in Auckland, Buenos Aires, Bochum, Cambridge, Duisburg, Oxford, and Philadelphia. His current research interests include collaborative innovation, organizational search, and learning from performance feedback. His recent contributions have been published in journals such as the Academy of Management Review, Journal of Applied Psychology, Journal of Management, Journal of Management Studies, Journal of Service Research, Information Systems Research, MIS Quarterly, Journal of Product Innovation Management, and Research Policy.

David Antons is a professor at the University Bonn and former co-director of the Institute for Technology and Innovation Management (TIM) in the TIME Research Area at RWTH Aachen University, Germany. He received his PhD from the same RWTH Aachen working in close cooperation with the university's Psychological Institute. He held visiting appointments at the universities of Cambridge and Melbourne. His research interests include knowledge sharing across organizational, spatial, and disciplinary boundaries; psychological influences on decision-making; individual learning from feedback; and text-mining approaches. His recent contributions have been published in journals such as Academy of Management Review, Academy of Management Perspectives, Information Systems Research, Journal of Management, Journal of Management Studies, Research Policy, Journal of Service Research, and Journal of Product Innovation Management.