Exploring Algorithmic Management Practices in Healthcare – Use Cases along the Hospital Value Chain

Research Paper

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Abstract. Algorithmic management (AM), the use of algorithms to handle coordination and control tasks traditionally performed by human managers, is being increasingly implemented in high-skill traditional industries, such as healthcare and finance. Embedding AM into existing organizational structures in traditional workplaces differs from previous forms of AM, challenging the generalizability of findings from the well-researched low-skill platform context. We conduct an exploratory interview study with nine semi-structured interviews to explore how AM is implemented in healthcare, particularly in hospitals. Our findings along the hospital value chain, including admission, diagnostics, treatment, and administration, reveal five use cases in which AM steers hospital workers: *patient intake management, bed management, doctor-to-patient assignment, workforce management*, and *performance monitoring and evaluation*. By shedding light on AM use cases in traditional industries, our study contributes to IS literature with a more nuanced perspective on AM while also providing practical implications for hospital administrators and healthcare professionals.

Keywords: Algorithmic Management, Healthcare, Hospital Value Chain, Qualitative Interview Study

1 Introduction

Across industries, such as healthcare, manufacturing, and finance, organizations are facing a growing shortage of skilled workers (Ferdous et al., 2022). At the same time, rapid advancements in computational capabilities, particularly those related to algorithmic systems, are transforming how work is organized and managed (Kumar et al., 2024). The intersection of these developments has fueled the emergence of algorithmic management (AM), a phenomenon in which algorithms coordinate, monitor, and control work processes that were traditionally overseen by human managers (Möhlmann et al., 2021). Initially, AM gained prominence in platform-based organizations, such as ride-hailing and food delivery services, as a central mechanism for value creation and workforce coordination. For example, gig economy platforms including Uber, DoorDash, and Upwork collectively manage over 180 million workers across Europe and the United States (Benlian et al., 2022). Apart from platform-based work, research on AM has examined low-skill work domains such as warehouses, with Amazon serving as a prominent example (Delfanti, 2021). In recent years, however, AM is no longer confined to platform or low-skill work but emerges in traditional, non-platform industries, where AM systems play a complementary role, working alongside human managers to coordinate the workforce (Benlian et al., 2022; Jarrahi et al., 2021). This development raises important questions about the transferability of existing knowledge from platform and low-skill work contexts to traditional, high-skill workplaces, highlighting the need for targeted research on AM in traditional industries (Cameron et al., 2023; Jarrahi et al., 2021). Despite the growing relevance, research on AM in traditional, high-skill industries remains limited. One critical domain of interest is healthcare, which is marked by complex coordination demands, workforce shortages, and high stakes in patient outcomes (Fichman et al., 2011; World Health Organization, 2025), conditions under which AM holds both great promise and high risk. By improving resource allocation and reducing cognitive workload, AM could alleviate existing pressure on overworked clinical staff while simultaneously introducing new forms of control and surveillance (Kojima et al., 2019; Rani et al., 2024). This makes healthcare a particularly relevant and challenging domain for the study of AM.

To address this gap, our study investigates how AM is applied within hospitals, a central institution in healthcare delivery. Hospitals represent complex, high-responsibility organizations in which the integration of algorithmic systems directly influences patient care, medical procedures, and administrative processes. To systematically analyze the use of AM in healthcare, we adopt a hospital value chain (Weimann et al., 2021), consisting of the four value chain steps: admission, diagnostics, treatment, and administration. This framework allows for a structured examination of AM use cases across key organizational functions. Against this backdrop, we pose the following research question: *How is AM implemented throughout different steps and activities across the hospital value chain?*

To examine this research question, we conducted an exploratory, qualitative interview study comprising nine semi-structured interviews, including seven doctors, two software providers, and one domain expert. Our findings, organized into three key themes corresponding to our hospital value chain steps, unveil five use cases in which AM directs hospital workers: *patient intake management, bed management, doctor-to-patient assignment, workforce management*, and p*erformance monitoring and evaluation*. Our study contributes to the growing body of research on AM by extending its analysis to traditional, high-skill industries, thereby moving beyond the predominant focus on platform and low-skill work. Specifically, we offer a more differentiated understanding of how AM can foster mutually beneficial outcomes for both organizations and workers. By viewing AM from an assemblage perspective, we deepen the theoretical understanding of its dynamics in real-world organizations, moving beyond simplified representations of single algorithms. Furthermore, we offer practical guidance and insights for hospital administrators, policymakers, and healthcare professionals.

2 Conceptional Background

2.1 Algorithmic Management

AM refers to “the large-scale collection and use of data […] to develop and improve learning algorithms that carry out coordination and control functions traditionally performed by managers” (Möhlmann et al., 2021, p. 2001). AM originates from platform-based organizations, such as Uber and Deliveroo, where digital technologies and algorithms are integral components and manage millions of workers through smartphone apps (Cameron et al., 2023; Wiener et al., 2021). IS literature has extensively studied these platform-based organizations as prime examples of AM being the sole management mechanism (e.g., Gal et al., 2020; Parent-Rocheleau & Parker, 2022). Although human managers are present, they are not perceived as part of the management system, leaving workers with no alternative forms of oversight. Consequently, workers often regard the algorithms as their true “bosses” (Hirsch et al., 2024; Möhlmann et al., 2021). AM differs structurally from human management by employing digital technologies (such as sensors and mobile devices) to delegate tasks, significantly reducing or even fully eliminating the need for human involvement (Benlian et al., 2022; Wiener et al., 2021).

In recent years, AM has expanded beyond low-skill platform work into high-skill traditional industries (Benlian et al., 2022; Jarrahi et al., 2021; Mateescu & Nguyen, 2019). This shift has been enabled by recent technological advancements, which now allow algorithmic systems to take over not only routine tasks but also complex, judgment-intensive activities traditionally performed by high-skilled workers (Acemoglu & Restrepo, 2018). In our study, we use the term low-skill work for standardized, routine, or manual tasks and high-skill work for non-routine, analytical, or interpersonal tasks requiring professional expertise (Acemoglu & Restrepo, 2018; Autor et al., 2003). In such high-skilled or traditional settings, organizations increasingly adopt AM to complement human managers rather than to replace them entirely (Hirsch et al., 2024; Wiener et al., 2021). This is an important distinction, as in this case AM is embedded in established power dynamics between the workforce and managers, leading to a redefinition of roles, relationships, and information flows (Jarrahi et al., 2021). While AM on platforms typically automates both decision-making and communication of managerial tasks (Parent-Rocheleau & Parker, 2022), traditional contexts often rely on algorithms solely to support decision-making while leaving their communication to humans (Jarrahi et al., 2021). Additionally, platform workers are independent contractors and not protected by most employment laws (Barati & Ansari, 2022). In contrast, traditional employees benefit from legal safeguards that reduce the risks of unfair and opaque algorithmic treatment. Given these key differences, results derived from research examining platform organizations may not be generalizable to traditional industries (Barati & Ansari, 2022; Jarrahi et al., 2021).

2.2 Algorithmic Management in Healthcare

Healthcare is an inherently high-stakes domain because, unlike other industries, it directly impacts human lives, often in critical and life-threatening situations (Fichman et al., 2011). AM in healthcare can significantly affect patient outcomes, medical accuracy, and raise ethical concerns (Grote & Berens, 2020). The complexity of healthcare, with its interplay of human expertise, patient well-being, and advanced technologies, calls for a careful exploration of how AM is implemented and what its potential consequences are (Amann et al., 2020; Grote & Berens, 2020; Rani et al., 2024). At the same time, healthcare currently faces critical challenges, including a worsening shortage of medical professionals and rising demand from an aging population with increasing care needs (Kojima et al., 2019; World Health Organization, 2025). To address these challenges, healthcare organizations have made significant investments in digital technologies, leading to the widespread adoption of advanced tools in clinical and administrative work (Rani et al., 2024). These developments include the adoption of algorithmic systems, which are employed to generate shift schedules and allocate staff efficiently (Topol, 2019). However, while such systems are often framed as tools for supporting healthcare delivery, their implementation and impact have yet to be systematically examined from an AM perspective. As healthcare staff are algorithmically managed through such systems, with their schedules, tasks, and medical procedures increasingly shaped or even dictated by algorithmic recommendations. As such, AM in healthcare represents not merely a technological innovation but a profound shift in how high-skilled work is organized and controlled.

To better understand AM in this complex domain, it is crucial to consider the multifaceted nature of the healthcare industry. According to Burns (2002), healthcare encompasses five major actor groups: payers (e.g., patients), fiscal intermediaries (e.g., pharmacies), providers (e.g., hospitals), purchasers (e.g., medical distributors), and producers (e.g., pharmaceutical manufacturers). Among these, hospitals (i.e., providers) serve as the central link between the physical supply side of healthcare (i.e., purchasers & producers) and the bureaucratic reimbursement system (i.e., payers & fiscal intermediaries). Furthermore, hospitals are the primary sites where patients, as care recipients, directly interact with healthcare services through diagnosis and treatment.

Given this pivotal role, we focus on hospitals as the subject of our study. Hospitals are complex organizations that encompass multiple interdependent primary activities (e.g., diagnostics and treatment) and support activities (e.g., human resources and administration). To systematically analyze how AM is integrated into these processes, we introduce an adapted hospital-specific value chain, which delineates the key process steps and allows us to identify where AM occurs and how it influences management practices, both clinical and administrative practices (Weimann et al., 2021). The resulting hospital value chain (see Figure 1) consists of three primary activities and one supporting activity, each of which is described in the following: admission, involving patient registration and initial assessment; diagnostics, encompassing medical tests and examinations to identify patient conditions; treatment, delivering clinical care aimed at improving patient outcomes; and administration, related to task coordination and ensuring adequate staffing.

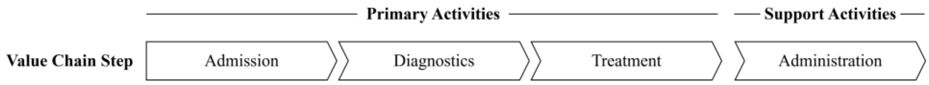

Figure 1. Hospital Value Chain (adopted from Weimann et al., 2021)

3 Methodology

3.1 Exploratory Study Design

To explore how AM is implemented throughout different stages and activities in the hospital value chain, we conducted an exploratory, qualitative interview study, following established guidelines (Myers & Newman, 2007). Our approach aligns with the qualitative research principles outlined by Kaplan & Maxwell (2005), as our inherently exploratory research question is framed as a “how” question, and we investigate AM within its real-life context without exerting control over events. To capture the prevalence of AM practices within healthcare, we focused our interview study on hospitals as our unit of analysis. Drawing on an extreme-case selection method, this allowed us to gain detailed insights into AM practices that are particularly pronounced and observable in such extreme contexts (Gerring, 2007). The high-stakes nature of hospitals, where decisions directly affect patient health and well-being, further supports our context selection. Our analysis was guided by the adapted hospital value chain, which provided a structured lens for systematically identifying AM use cases across primary and support activities.

3.2 Data Collection

To collect data, we conducted nine semi-structured interviews. Based on the principle of purposeful sampling (Patton, 2002), we included seven doctors for their practical experiences, two software providers to understand system design and one domain expert for broader contextual insights. Each doctor was affiliated with a different hospital to ensure broad coverage and capture diverse AM practices (see Table 1 for an overview of interview participants). We then employed a code frequency counts approach, whereby our analysis indicated that saturation was reached after seven interviews, as no new codes emerged beyond this point, confirming the adequacy of our sample size (Hennink & Kaiser, 2022). The semi-structured nature of the interviews allowed us to ask follow-up questions and clarify misunderstandings (Adams, 2015). Our interviews each had a duration of 20 to 40 minutes. Throughout the different interviews, we refined our interview guide to include more precise follow-up questions (e.g., “Does a digital system evaluate your work productivity?”). The initial topics in the interview guide focused on known technologies (e.g., workforce management systems) in hospital workflows. As the interviews progressed, our interest shifted toward specific use cases (e.g., performance monitoring and evaluation) that emerged as AM.

Table 1. Overview of Interview Partners

Interview Partner	Age (years)	Workplace	Profession	Work Experience (years)
D1	34	Hospital	Doctor	7
D2	53	Hospital	Leading senior doctor	26
D3	52	Hospital	Medical director department of radiology	26
D4	28	Hospital	Doctor	4
D5	29	Hospital	Assistant doctor department of radiology	2
D6	29	Hospital	Assistant doctor department of radiology	5
S1	25	Company	Co-founder, software provider	3
S2	30	Company	CEO, software provider	4
E1	56	Research Lab	Senior economist and researcher	34

The interviews were conducted and recorded via video conferencing tools and transcribed afterwards. In preparation for the interviews, the authors familiarized themselves with general hospital work processes and commonly used healthcare software tools. To ensure comparability, at least two authors were present across all interviews. All recordings were transcribed and translated from German into English to allow for direct quotations and linguistically smoothed to enhance clarity and understanding while preserving the integrity of participants' statements. Thereby we followed established guidelines for transcribing interviews to preserve the correctness of the data (Oates, 2006).

3.3 Data Analysis

Our study employed thematic analysis due to its systematic yet flexible approach to analyzing qualitative data, enabling us to explore interviewees' experiences and perspectives (Clarke & Braun, 2017). All transcripts were independently coded by at least two authors to ensure reliability, utilizing the tool MAXQDA. For data evaluation, we employed a combined approach, integrating deductive concept coding and inductive open coding (Saldaña, 2009). Specifically, the value chain steps were employed as guiding concepts for the deductive concept coding process. Additionally, relevant text passages and identified AM use cases that did not fall under existing categories were assigned new codes through inductive open coding (e.g., bed management, performance monitoring and evaluation). Next, the coded segments were iteratively analyzed and synthesized into research propositions. Once the authors reached unanimous agreement, three themes were established.

4 Findings

Figure 2 presents the identified AM use cases along the hospital value chain, which are described in detail in the following sections.

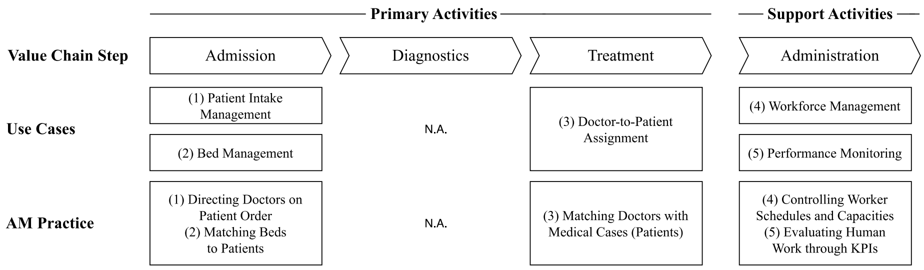

Figure 2. AM use cases along the hospital value chain

4.1 Theme 1: AM Practices Streamline Admission Processes in Hospitals

In admission, the first step in the hospital value chain, we identified two distinct use cases of AM. First, *patient intake management* enhances the initial evaluation of incoming patients through algorithmic analysis of symptoms, medical history, and other relevant indicators. By ranking patients based on urgency, the algorithm ensures severe cases receive faster diagnosis and treatment, significantly impacting patient order management previously handled by doctors and staff. Thus, we classify the system as AM because it directs doctors to specific patients and consequently manages their work sequence. One doctor explained, *"This new tool would introduce a preliminary screening [...] It could identify pathologies in advance, prioritize cases, and move them higher up on the diagnostic list."* (D5). This structured assessment reduces reliance on manual triage, minimizing human error and delays while optimizing resource allocation. Doctors and nurses receive a pre-sorted patient list, ensuring that their focus is directed toward the most critical cases, which is facilitated through color-coded urgency indicators, as one doctor described, *"Red for 'review immediately,' green for 'can wait'. This facilitates prioritization so that time-critical findings are processed more quickly."* (D5). By standardizing urgent decisions and automating prioritization, the system enhances efficiency while reducing staff's administrative burden.

Second, *bed management* covers assigning hospital beds and streamlining how incoming patients are matched with available resources. This use case represents AM as it directs hospital staff in their daily tasks of assigning and transferring patients to their designated rooms. As one software provider described, "*When the patient arrives at the hospital [...], they are assigned an expected stay duration. This duration appears in the 'unoccupied' field. The user then clicks 'auto-assign,' and all patients with the 'unoccupied' status are automatically assigned beds. This serves as a suggestion that the user confirms afterward*." (S2). Rather than coordinating bed assignments manually, the system integrates this task algorithmically, significantly reducing the time spent on administrative planning. The software provider emphasized the time-saving effect per patient: *"Manually, this process would take 20 minutes, but now it's integrated and automatic."* (S2). Bed management replaces manual coordination, previously involving multiple staff and frequent phone calls, by managing the resource "bed" and directing medical staff on their work of where to move the beds. The same software provider estimated, *"Compared to the current status quo, the improvement can be up to six hours per day per ward. This time is spread among all staff involved. Additionally, up to nine phone calls per patient transfer, which are currently necessary, can be eliminated."* (S2). Beyond time efficiency, this AM system also enhances hospital occupancy rates by preventing inefficiencies caused by incomplete or outdated bed allocation information. According to the software provider, *"Hospitals in Germany are only 70% occupied on average, partly due to staffing shortages but also because of poor coordination. We managed to increase occupancy by 5% in one hospital, which translates to €400,000 more revenue annually for an average hospital."* (S2). The system's impact extends beyond efficiency for hospital management and staff. As the software provider further explained, *"Management focuses on numbers like revenue and occupancy rates, [...] but for the people using the system, it's more about reducing stress and minimizing time spent on administrative tasks. [...] They'd rather focus on patient care."* (S2).

4.2 Theme 2: AM Practices in Treatment Handle Doctor-to-Patient Assignment

A use case of AM in the treatment phase of the hospital value chain is *doctor-to-patient assignment*. Traditionally, assignments from doctors to patients were handled ad hoc and manually, relying on a general list without structured criteria. The introduction of an algorithmic system has changed this process by considering multiple factors such as a doctor's expertise, specialization, availability, and working hours. This constitutes AM, as it directs staff by dictating their next patient. One doctor described this phenomenon, stating, *"Previously, everything was unspecific and organized in a single list. Now, the system automatically assigns cases, considering factors like the experience level of the doctors, the types of examinations they can perform, and their working hours. It informs the medical-technical assistants which doctor to assign."* (D6). By dynamically allocating doctors based on these criteria, the system ensures that each case is handled by the most appropriate professional. This is confirmed by the domain expert, who emphasized the impact on patient care quality: *"Leveraging this information, the system could help assign patients to the doctors best suited for them, ultimately leading to better outcomes."* (E1). Beyond initial assignments, the system also enhances continuity of care, a critical factor for treatment effectiveness. The same expert highlighted this aspect, stating, *"Another major benefit of this automated system was improving follow-ups. Once a patient had seen a particular doctor, the system ensured that their follow-up appointment was scheduled with the same doctor whenever possible. Often, patients see one doctor initially but a different doctor for their next visit, which can create anxiety and disrupt continuity of care."* (E1). This prevents treatment disruptions and reduces anxiety, as patients are not forced to repeatedly explain their medical history to different doctors.

4.3 Theme 3: AM Practices Support Hospital Administration

In the last step of our value chain, we identified two use cases of AM. First, in *workforce management*, algorithmic systems facilitate task allocation and scheduling. As one doctor noted, "*There are numerous areas of application, such as shift scheduling or administration.*" (D2). These practices are a form of AM, as they delegate coordination tasks from human managers to algorithmic systems. Instead of supervisors manually assigning work, the system analyzes real-time data, such as task urgency, worker availability, and operational constraints, to determine optimal allocation. By reshaping this process, algorithmic task allocation structures workflows, directs worker actions, and enforces predefined rules, ensuring efficiency and consistency in task distribution. Traditionally, doctors manually assigned tasks among themselves, often leading to inefficiencies. This has changed with the introduction of AM systems, as one doctor described, *"Previously, each doctor had to assign tasks themselves, leading to unequal workloads. Now, an algorithm ensures fair distribution. Medical assistants just click 'process' and the algorithm creates a personalized task list for each doctor."* (D6). By adjusting assignments dynamically based on workload and capacity, AM systems reduce individual burdens and optimize departmental efficiency. The doctor further highlighted the practical effect of this system: *"To be honest, this results in me having significantly less to do in day-to-day life because I no longer need to cover for others."* (D6). However, in contrast to these positive assessments, another doctor emphasized the pressure that algorithmic systems can exert on individual workflows: "*It is important to work in a time-oriented manner. If I don't finish my work within the defined timeframe, I end up working overtime, and that's obviously frustrating.*" (D4). Furthermore, AM supports hospitals in managing unforeseen disruptions, such as last-minute schedule changes. As a doctor explained, *"If the surgeon calls in sick in the morning, a person would normally have to redo the entire plan. [...] With one click, the algorithm generates the best possible new plan."* (D6). This adaptability ensures operational continuity and reduces downtime, leading to significant efficiency gains. *"Compared to the status quo, the improvement amounts to six hours saved per day per station,"* (S2) noted one software provider. In addition to assigning tasks, AM also standardizes the execution process itself. As one doctor described, *"The system forces me to work through it step by step"* (D3), highlighting how algorithmic systems not only allocate work but also manage its sequencing and structure, thereby imposing routines and reducing individual flexibility.

The second use case in administration is *performance monitoring and evaluation*, where algorithmic systems track key performance indicators (KPIs) at the departmental level. These AM systems analyze metrics such as the time required for image analysis, diagnosis, report completion, and error rates, thus evaluating human work, making them a form of AM. A software provider confirmed this, stating, *"Of course, we calculate such KPIs. For example, we look at the most common errors in the emergency department"* (S1*).* A doctor described this practice: *"There are overarching statistics, like how long it takes to release a report or the time from image acquisition to diagnosis."* (D5). By providing structured insights, these tools support adherence to performance standards and enable department heads to monitor efficiency. However, the transparency of such evaluations for individual clinicians remains limited. One doctor reflected on this, stating, *“We are informed by our chief doctors afterward whether everything met the standards. [...] I assume most of this evaluation is conducted by a program.”* (D5). Another doctor referred more directly to the technical infrastructure behind such evaluations, explaining, *“Performance monitoring is implemented […] through dashboards [that] show who has done how much.”* (D1). This contrast illustrates how AM can operate with a high degree of visibility for management while remaining opaque to those being evaluated.

5 Discussion

Our study shows that AM in healthcare can lead to operational efficiency by streamlining workflows and reducing bureaucratic tasks. At the same time, AM redefines how work is organized by embedding managerial logic into algorithmic systems, shifting control from staff to systems and curtailing professional autonomy, which is also observed in low-skill work like ride-hailing (Möhlmann & Zalmanson, 2017). This is particularly evident as task allocation, sequencing, and evaluation are increasingly handled by algorithms. Thereby, a surprising and divergence pattern emerges. Some staff experienced reduced workload due to fairer task distribution, which is rarely reported in the low-skill work context, where AM typically increases demands (Cram et al., 2022). Yet even in healthcare, other participants also reported increased pressure from rigid schedules and time-bound expectations, challenging the notion that AM delivers uniform efficiency gains across individuals. This underscores that workforce planning in healthcare is complex due to interdependencies between qualifications, task types, and staffing dynamics (Erhard et al., 2018). Moreover, performance monitoring enhances managerial oversight but lacks transparency, creating tensions between organizational targets and staff well-being.

Compared to low-skill domains, we confirm that AM in hospitals does not replace managers but complements them by embedding algorithmic logic into existing structures (Jarrahi et al., 2021; Wiener et al., 2021). However, AM still influences critical aspects of care delivery by dictating the order and timing of patient interactions and matching doctors to patients. These algorithmic decisions carry substantial implications: if a patient with urgent needs is deprioritized or a doctor is assigned beyond their specialization, questions of responsibility emerge (Lüthi et al., 2023), particularly when such mismatches lead to adverse outcomes.

5.1 Theoretical Contributions and Practical Implication

Our study provides three significant theoretical contributions and one crucial practical implication. First, we advance the understanding of AM in the understudied context of traditional industries (Benlian et al., 2022; Cameron et al., 2023). While the importance of exploring AM beyond platform work has been emphasized in existing literature (e.g., Jarrahi et al., 2021; Wiener et al., 2021), research in high-skill domains remains scarce. To the best of our knowledge, aside from Rani et al. (2024), we are among the first to examine AM in the healthcare industry, thereby extending prior research that has largely focused on low-skill work domains such as warehousing and platform-based gig work. By investigating AM in a high-skilled, non-platform setting, we broaden the scope of AM research. This is important because AM unfolds differently in high-skill domains, where ethical considerations and expertise play a critical role in daily work practices. Unlike in low-skill and platform-based work, AM in traditional, high-skill work is less critical to the central business model or entire workflows but rather acts as a support to existing processes and unfolds in specific use cases only. Examining AM in this domain allows us to capture the specific opportunities that arise when algorithms interact with complex, high-responsibility work, providing a richer and more differentiated understanding of AM practices in traditional workplaces.

Second, we challenge earlier portrayals of AM as primarily beneficial to organizations and unfavorable to workers (Möhlmann & Henfridsson, 2019). Our findings align with more recent IS research suggesting that AM can foster mutually beneficial outcomes for organizations and workers (Benlian et al., 2022). Specifically, interviewees reported positive behavioral experiences with AM systems, such as reduced stress and a stronger sense of fairness and reliability in their daily workflows. Previous research has often focused narrowly on conceptual and sociotechnical aspects of AM (Hirsch et al., 2023; Jarrahi et al., 2021; Wiener et al., 2021), while leaving its broader organizational impacts on processes and outcomes underexplored. Our findings expand into an organizational perspective, indicating that hospitals benefit, for instance, from increased efficiency and optimized resource allocation, contributing to higher revenues. This finding is particularly relevant, as it provides a more balanced view of AM that moves beyond a one-sided, negative perspective of highlighting worker control and surveillance as consequences of AM. By showing how AM can simultaneously improve organizational outcomes and support workers, we shed light on the double-sided benefits that AM provides as it becomes part of a socio-technical mechanism for workers within organizations.

Third, our study responds to calls for shifting the focus of AM research beyond single-algorithm analyses (Cameron et al., 2023). By adopting an assemblage perspective, we reveal how multiple interconnected algorithms sometimes jointly shape workflows and staff coordination within hospitals. Thereby, we offer a more nuanced understanding of AM in complex organizational settings, thus, our findings suggest that AM rarely operates through isolated systems in practice. It either emerges from the interaction of diverse algorithmic tools that influence and reinforce each other or operates jointly with human workers. By conceptualizing AM as an assemblage, we advance the theoretical understanding of how AM unfolds in real-world organizations, moving beyond simplified depictions of AM as a standalone system and enabling future research to capture the full complexity of AM as an evolving form of management in organizational contexts.

As a practical implication, our findings offer actionable insights for policymakers, hospital administrators, and healthcare professionals by identifying key AM use cases that hospitals can adopt and which highlight the need to actively govern AM adoption to balance efficiency gains with staff well-being and patient safety. Our findings show that AM can enhance operational efficiency by enabling faster workflows, higher resource utilization, and more effective resource allocation, supporting a more structured and data-driven approach to hospital processes. However, the increasing reliance on algorithmic systems raises concerns regarding transparency, professional autonomy, and ethical considerations, particularly in areas such as performance monitoring and algorithmic recommendations. These insights call for balanced implementation strategies that harness AM's efficiency gains while ensuring explainability, flexibility, and human oversight in managing workflows and staff interactions. To achieve this, hospitals and policymakers should prioritize transparent communication about the role and limitations of AM, provide training and upskilling opportunities to ensure medical staff can effectively work alongside algorithmic systems, and establish internal oversight mechanisms to monitor and evaluate AM's impact on clinical workflows. Moreover, adopting participatory approaches in design and implementation, involving healthcare professionals in the development and refinement of AM tools, can help align these technologies with real-world needs while fostering trust and acceptance.

5.2 Limitations and Future Research

As with any other research, our study as well has several limitations that should be considered when interpreting the findings. First, all interviewees were based in German-speaking countries, which limits the geographical generalizability of our findings. Reproducing this study in different countries and exploring its application in other high-stakes domains (e.g., finance) could provide valuable insights into broader implications of AM systems across various organizational and cultural contexts. Second, while we interviewed a variety of key stakeholders in hospitals, our interviewees do not represent all professional groups in hospitals. Future research should examine AM's impact on different staff groups to gain a better understanding of role-specific effects. Finally, the data collected through interviews may be subject to biases typical of self-reported data, such as social desirability bias or acquiescence bias (Podsakoff et al., 2003). Interviewees may have unintentionally misattributed outcomes to AM systems or presented their experiences in a more favorable light. To address this, future research could incorporate quantitative methods (e.g., field experiments) and utilize performance metrics (e.g., patient throughput) to validate and complement the qualitative insights.

6 Conclusion

AM has the potential to fundamentally reshape work practices, not only in platform-based businesses but also in well-established work domains, such as healthcare. Our study offers an important starting point for understanding AM practices in hospitals and reveals potential benefits and drawbacks. As AM becomes more integrated into healthcare, research should continue examining how AM systems can further enhance efficiency while preserving professional autonomy and enhancing the future of work in healthcare delivery.

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