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# Reconfiguration of uncertainty: Introducing AI for prediction of mortality at the emergency department

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ABSTRACT

The promise behind many advanced digital technologies in healthcare is to provide novel and accurate information, aiding medical experts to navigate and, ultimately, decrease uncertainty in their clinical work. However, sociological studies have started to show that these technologies are not producing straightforward objective knowledge, but instead often become associated with new uncertainties arising in unanticipated places and situations. This study contributes to the body of work by presenting a qualitative study of an Artificial Intelligence (AI) algorithm designed to predict the risk of mortality in patients discharged to home from the emergency department (ED). Through in-depth interviews with physicians working at the ED of a Swedish hospital, we demonstrate that while the AI algorithm can reduce targeted uncertainty, it simultaneously introduces three new forms of uncertainty into clinical practice: epistemic uncertainty, actionable uncertainty and ethical uncertainty. These new uncertainties require deliberate management and control, marking a shift from the physicians' accustomed comfort with uncertainty in mortality prediction. Our study advances the understanding of the recursive nature and temporal dynamics of uncertainty in medical work, showing how new uncertainties emerge from attempts to manage existing ones. It also reveals that physicians' attitudes towards, and management of, uncertainty vary depending on its form and underscores the intertwined role of digital technology in this process. By examining AI in emergency care, we provide valuable insights into how this epistemic technology reconfigures clinical uncertainty, offering significant theoretical and practical implications for the integration of AI in healthcare.

## 1. Introduction

Various sophisticated digital technologies are often developed with the promise to help navigate and ultimately decrease uncertainty in clinical work, diagnosis and treatment (Armstrong and Hilton, 2014). A major promise behind many of these digital technologies, such as imaging devices or genetic tests, is that with the novel and more accurate information they produce, medical experts are able to arrive at a more objective and unequivocal diagnosis and therefore prescribe more precise and effective treatment (Racine et al., 2005). Imaging technologies, such as X-ray, Computed Tomography-scanners (CT) or Magnetic Resonance Imaging (MRI), have been heralded in the media and in the medical literature as the "gold standard" for producing superior and objective knowledge about human anatomy and its functions (Burri, 2008; Joyce, 2008; Saunders, 2008). Another recent and persuasive example, and the focus of this paper, is artificial intelligence (AI), which is broadly understood as a general-purpose technology based on a core set of capabilities and computational algorithms designed to mimic and outperform human cognitive function to analyze complex data (Shaw et al., 2019). Claimed and portrayed as possessing the principal strengths of automation, accuracy, and objectivity, the hopes and expectations attributed to AI for reducing uncertainty in clinical work are substantial (Chen and Decary, 2020; Gama et al., 2022; Topol, 2019).

However, and based on the longstanding tradition of demonstrating how uncertainty is inherent in medical practice, and how medical experts need to learn to manage uncertainty (Atkinson, 1984; Fox, 1957, 1980, 2000; Light, 1979; Swoboda, 2008), sociological studies have started to show that after being introduced in practice, digital technologies are not producing straightforward objective knowledge, and often result in increased uncertainty around interpreting technologically mediated results. Thus, when examining the introduction of new digital technologies in practice, it is important to anticipate that technology-driven responses to uncertainty create new uncertainties in unanticipated places and situations; it is thus also important to explore

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such uncertainties as part of the introduction of the new technologies (Bailey et al., 2019; Timmermans and Buchbinder, 2013). A sociological exploration is a particularly well-suited approach for embarking on such endeavors, as it is sensitive to potential unintended consequences that follow the introduction of new digital technology, and in particular the social situations where views on and experiences of uncertainty unfold in practice (Timmermans and Buchbinder, 2013).

While existing sociological studies on uncertainty in medical work have provided several important insights, e.g., for our understanding of uncertainty in relation to patients, residents in training, and the interactions between clinicians and patients, we know less about how physicians experience and manage uncertainty in clinical settings and in relation to the intertwined role of digital technology (Diamond-Brown, 2016; Mackintosh and Armstrong, 2020; Timmermans and Berg, 2003), particularly regarding AI in emergency care (Kuiper et al., 2022; Miao et al., 2020). We focus on AI as a technology that is generally less empirically studied in professional contexts and in relation to uncertainty (Bailey et al., 2019; Faulconbridge et al., 2023). AI is often positioned as "an epistemic technology" pertaining to the production and evaluation of knowledge claims (Anthony, 2018; Knorr-Cetina, 1999), giving the impression of providing increased certainty, precision and control (Chen and Decary, 2020; Han et al., 2011). Thus, AI's main task, unlike other often studied digital technologies such as IT systems, is not to facilitate data and information but rather to interpret it and take part in the construction of new knowledge, all to assist with input to healthcare professionals' core medical tasks (Benbya et al., 2020). In addition, emergency care is a critical setting riddled with complexity, stress, and uncertainty, but has also been subject to considerable technological developments intended to deal with these constraints (Heath et al., 2003; Miao et al., 2020; Nugus et al., 2011). These additions to previous research are important because they enable a more nuanced understanding of life-and-death uncertainty in relation to disruptive and novel digital technologies.

Thus, to advance our knowledge of this topic, we pose the following research question: *How is the experience and management of uncertainty in clinical work affected by the introduction of AI in practice?* To answer this question, we present a qualitative study of an AI-based algorithm developed and intended to predict the risk of mortality in patients discharged to home from the emergency department (ED). This technology was designed to help emergency physicians with the well-known struggles around assessing how sick patients really are, and predicting the risk of mortality, an uncertainty that often contributes to unnecessary interventions and treatments (Kennedy et al., 2014). Based on in-depth interviews with healthcare professionals working at an ED of a Swedish hospital, we demonstrate how the AI algorithm had the potential to reduce the targeted uncertainty, but also how it simultaneously brought three new forms of uncertainty into clinical practice, i.e., epistemic uncertainty, actionable uncertainty and ethical uncertainty.

In showing this, our study makes three main contributions. First, it contributes to the literature on uncertainty in medical work by advancing understanding of the recursive nature and temporal dynamics of uncertainty, illustrating how new uncertainties emerge when trying to manage existing ones. Second, it contributes to the literature on attitudes towards and management of uncertainty in medical work by showing that these attitudes vary depending on the different forms of uncertainty and by highlighting a transition from reflexive to more controlled approaches. Third, it contributes to the literature on the intertwined role of digital technology in relation to uncertainty by providing new insights specifically on AI, demonstrating that while AI can reduce some uncertainties, it also introduces new forms that require different management strategies. This third contribution also emphasizes the concept of overflow, where an excess of information from AI can exacerbate uncertainty, necessitating new approaches to manage this overflow.

The article is structured as follows: first, a literature review is presented; next, the research setting and method are described, followed by the findings; then a discussion follows; and finally, the key contributions, implications for practice, and suggestions for future research are elucidated.

## 2. Literature review

Uncertainty has been studied extensively across various disciplines, both in and outside of the healthcare domain, each offering unique insights into its nature and implications (Argote, 1982; Hillen et al., 2017). In organizational studies, for instance, a common focus has been on uncertainty in relation to decision-making. Researchers have examined how outcome uncertainty affects decisions about introducing new practices (Nilakant and Rao, 1994), and how input uncertainty influences the adoption of coordinative practices (Argote, 1982). This body of work highlights the aversive nature of uncertainty, a negative state that individuals strive to reduce or eliminate due to its association with incomplete information or knowledge, making it challenging to predict future states and discern effort-outcome relationships. However, recent research suggests that uncertainty can have positive aspects, such as fostering adaptability and innovative problem-solving, and driving growth and improvement by being viewed as a learning opportunity rather than a threat (Constantinides et al., 2024; Griffin and Grote, 2020).

In relation to medicine and medical work, social scientists have widely discussed the notion of uncertainty, and despite their different approaches to the concept, they seem to agree that it is a foundational feature of medical practice (Fox, 1980, 2000; Moreira et al., 2009; Timmermans and Angell, 2001). This is because medical knowledge and practice are riddled with various unknowns, and the number of medical facts is a moving target, impossible to completely master (Fox, 1957). While medical sociologists and social scientists universally acknowledge that uncertainty is inherent in medical practice, they diverge in their views on its dominance and how medical experts experience and manage it. One perspective, represented by scholars like Fox, emphasizes the intrinsic and pervasive nature of uncertainty in medicine. Fox's seminal work highlights that medical training imbues practitioners with a professional attitude of objective expertise and detached concern, allowing them to manage the inherent uncertainties of clinical practice (Fox, 1980, 2000). This perspective suggests that medical professionals develop a comfort with uncertainty through experience and socialization, leading to a culture of uncertainty where they learn to live with and reflexively address the unpredictable aspects of their work (Fox, 1957, 1980, 2000). More recent studies support this view, indicating that physicians have learned to manage and live with uncertainty, developing a sense of comfort over time (Bochatay and Bajwa, 2020; Ilgen et al., 2019). In contrast, another perspective, led by authors such as Light and Atkinson, argues that alongside training for uncertainty, there is a concurrent and significant emphasis on training for control. Light (1979) and Atkinson (1984) contend that medical training also focuses on mastering uncertainties by acquiring relevant knowledge, technical expertise, and autonomy. This approach fosters an attitude of control and dominance over uncertainty, suggesting that medical practice involves not just coping with, but actively seeking to eliminate uncertainties where possible. These scholars critique the notion that uncertainty is the primary hallmark of medical practice, positing instead that a dogmatic, control-centered form of medicine is equally prevalent. Therefore, while both perspectives agree on the presence of uncertainty in medicine, they differ on its dominance and the methods by which medical professionals manage it—either by embracing and adapting to uncertainty or by striving to control and minimize it.

Given that uncertainty influences various facets of medical work, such as diagnosis, prognosis and treatments (Han et al., 2017; Timmermans and Angell, 2001), sociological studies on this uncertainty have focused on several aspects. First, by describing how patients and relatives deal and live with uncertainty related to, for example, unexplained symptoms (Nettleton, 2006), rare conditions requiring surgery (Hinton and Armstrong, 2020), and ambiguous diagnostic tests and diagnoses (Reed et al., 2016; Whitmarsh et al., 2007). Second, by highlighting how residents manage uncertainty in their training (Atkinson, 1984), e.g., by engaging in a continuous process along evidence-based clinical judgment (Timmermans and Angell, 2001) and by learning to reproduce their supervisors' attitudes towards uncertainty (Bochatay and Bajwa, 2020). Third, by showing how uncertainty manifests and is dealt with in patient-doctor interactions, e.g., by setting reasonable expectations and preserving space for hope (Kuiper et al., 2022), by conceptualizing uncertainty indirectly and in a depersonalized manner (Lian et al., 2021), and by physicians and patients coming together to develop novel ways to interpret borderline screening results (Timmermans and Buchbinder, 2010).

While these studies have provided valuable insights, we know less about how physicians experience and manage uncertainty in clinical settings and in relation to the intertwined role of digital technology (Diamond-Brown, 2016; Mackintosh and Armstrong, 2020; Timmermans and Berg, 2003). Clinical uncertainty is a useful label here as it refers to situations where it is not clear for specialists, because of lack of knowledge or reassurance, how to proceed (see Fox, 2000; Ducey and Nikoo, 2018). Thus, specific attention is paid to uncertainty in relation to how expert work is performed among medical specialists, and not on how uncertainty is dealt with in doctor/patient interactions (e.g., Stivers and Timmermans, 2016). Clinical uncertainty occurs in various situations, for example when none of the existing evidence allows the clinician to definitely rule out any of the possible solutions, such as when it is not clear from history and laboratory findings if a patient is suffering from one or another disease (e.g., Kennedy et al., 2014), or when a radiologist detects changes in images but is unsure what these changes mean (Burri et al., 2014).

The role of technology is central here: various medical technologies—such as imaging devices or genetic testing—continue to be developed and introduced with the aim of alleviating uncertainty, by offering experts novel and more accurate information and thereby enabling them to take more objective, evidence-based action and make unequivocal judgments (Armstrong and Hilton, 2014; Joyce, 2005; Reed et al., 2016). A classic example of technology alleviating clinical uncertainty is the stethoscope, considered to be the first diagnostic instrument to allow physicians to obtain knowledge about disease that was more "reliable" than "subjective" patient descriptions of their symptoms (Schubert, 2011). More recently, imaging technologies such as MRI and CT have been heralded for producing superior and objective knowledge about human anatomy and its functions (Joyce, 2005). By offering a direct visualization of human anatomy, these technologies extend the "medical gaze" into areas of the body inaccessible to unmediated forms of medical examination (Burri, 2012; Joyce, 2008; Prasad, 2005), with the potential to further alleviate clinical uncertainty. The use of MRI for diagnostic pregnancy, for example, allows visualizing an entire fetus, delivering more in-depth insight into pregnancy development for patients and physicians (Reed et al., 2016). Genomic technologies are another example of technology that can alleviate uncertainty by offering not only diagnostic, but also prognostic and predictive information, by allowing estimates of the chance of breast cancer tumor recurrence and treatment response (Bourret et al., 2011).

At the same time, many studies focus on the technological aspects of uncertainty, highlighting how the complexity and volume of information generated by new digital technologies can create new challenges and ambiguities in clinical practice. Once such digital technologies are introduced in practice, this new information can lead to different kinds of epistemic issues, increasing ambiguity with respect to appropriate clinical action and thus increasing uncertainty (Timmermans and Buchbinder, 2013; Bourret, 2005; Bourret and Cambrosio, 2019). For example, the introduction of prenatal ultrasound screening created new forms of uncertainty, including complex risk, and ambiguous diagnostic information, leading to prolonged and repeated inconclusive testing and associated dilemmas for clinicians (Williams, 2006). Similarly, the introduction of molecular diagnostics into clinical settings increased the precision and extent of measuring genetic profiles, but the huge amount of information that followed increased uncertainty (Bourret et al., 2011). With the new prognostic information from molecular diagnoses, it became unclear what such results should signify, and who had the required expertise to make use of the technology and the new information (Bourret et al., 2011). And although MRI is often discursively associated with transparency, certainty, and objectivity (Joyce, 2005), studies of this technology have shown that MRI images rely on more-intense engagement and interpretation by radiologists, whereby their judgments become even more crucial (Burri, 2008, 2012; Tyskbo and Sergeeva, 2022). In a study of newborn screening technologies, Timmermans and Buchbinder (2010) found that while this novel technology was expected to provide accurate knowledge and certainty about whether a child had a metabolic disorder, it in fact led to increased uncertainty, where clinicians and parents struggled to interpret borderline results and determine whether they had sufficient knowledge for a specific situation.

While these studies have started to illustrate the complex relationship between technology and uncertainty, indicating that technologies designed to reduce uncertainty can sometimes have the opposite effect or give rise to new uncertainties, there is a notable gap in the literature concerning AI and uncertainty. AI is particularly relevant in this context as an epistemic technology less empirically studied in professional settings (Bailey et al., 2019; Faulconbridge et al., 2023; Sharma et al., 2022), distinct from other digital systems in its role of producing and evaluating knowledge and information (Anthony, 2018; Knorr-Cetina, 1999). AI is perceived as enhancing certainty, precision, and control (Chen and Decary, 2020; Han et al., 2011) and is crucial because the absence of information and knowledge is often viewed as a source of uncertainty. Unlike IT systems designed primarily for data storage and retrieval, AI interprets data and contributes to creating new knowledge, supporting healthcare professionals in their core tasks (Benbya et al., 2020). However, as Berente et al. (2021) summarize, AI's major characteristics—such as autonomy, learning, and inscrutability—introduce complex and often contradictory effects. These features can indeed enhance decision-making capabilities, but they also create new forms of uncertainty, particularly when the decision-making processes of AI are opaque or difficult to interpret. This opacity is not just a technical issue but also a social one, as it affects how users interact with, understand, and trust AI systems. As observed in other high-uncertainty task contexts, such as autonomous driving, AI systems, despite their advanced capabilities, are rife with challenges as they can often introduce new forms of uncertainty that require careful human oversight (Constantinides et al., 2024). Thus, it is suggested that AI's role in producing and evaluating knowledge can both alleviate and exacerbate uncertainty, depending on how it is managed. This unique role highlights AI's importance in the context of technological uncertainty and the need for further empirical investigation. Additionally, previous studies have not adequately explored how the two perspectives on uncertainty mentioned earlier—attempting to control it or developing comfort with it—relate to technology. Understanding how these two perspectives on uncertainty interact with AI is vital in order to develop deeper insights into the technology's impact on medical practice and its potential to either reinforce comfort with uncertainty or enhance control over it. This is especially relevant given that previous research from other high-uncertainty task contexts has shown that users' acceptance and attitudes towards technology are impacted by their level of uncertainty tolerance (Griffin and Grote, 2020). For example, in their study on autonomous driving, Constantinides et al. (2024) illustrated that individuals with lower uncertainty tolerance tend to intervene with and control AI systems more frequently in real-time and are limited in their exploration of AI systems over time. In contrast, those with higher tolerance might rely more heavily on AI, potentially leading to overconfidence and complacency in real-time, but also to joint learning in task performance over time as they exploit their own knowledge while exploring the capabilities of AI systems. This underscores the complex dynamics between AI and uncertainty.

Thus, in this paper, we join and advance current research by focusing specifically on an aspect that is relatively less explored in existing studies of technology and uncertainty—how the potential for new knowledge offered by new AI technologies triggers changes in the experience and management of uncertainty in clinical work. Furthermore, by investigating AI in the specific setting of emergency care, a setting riddled with uncertainty and subject to considerable technological advancements, we aim to uncover how this epistemic technology impacts the overall experience and management of uncertainty among medical professionals in life-and-death situations.

## 3. Research design

To capture how the introduction of new digital technology impacts uncertainty among physicians in clinical practice, a qualitative case study was deemed appropriate (Yin, 2003). We selected our case given that we knew there was a tangible and pronounced ambiguity in the work of the physicians and where an AI algorithm had been developed as a way to manage this—thus constituting a revelatory setting wherein the dynamics of interests would be more transparent (Patton, 1990). As such, our case study was largely defined by using the logic of selecting an information-rich case (Lincoln and Guba, 1985).

Furthermore, as this algorithm has only recently been presented and introduced to emergency physicians, we had a unique opportunity to capture physicians' experiences and reflections in-situ, thus reducing the risk of recall bias associated with retrospective data (Skowronski et al., 1991). With this real-time approach (Pettigrew, 1990) we also expected emergency physicians (EP) to disclose negotiations and controversies, necessitating them to articulate the reasons behind their thinking and behavior.

### 3.1. Setting and AI algorithm

Region Halland, a county council located in western Sweden, has invested in a sophisticated healthcare analysis and research platform named the Regional Healthcare Information Platform (RHIP). This platform is intended to expedite clinical and management assessments, as well as research endeavors (Ashfaq et al., 2020). RHIP comprises a meticulously curated, filtered, and pseudoanonymized subset of data drawn from diverse patient and administrative repositories. These data sources encompass more than 20 regional IT systems and national registries. To facilitate the analysis of healthcare data, the Center for Information-Driven Care (CIDD) was established as a central facility within Region Halland. CIDD's role involves analyzing, simulating, and evaluating the consequences of healthcare system alterations at a systemic level. This encompasses the evaluation of both quality and cost-related aspects. In response to the structured data housed in RHIP, CIDD developers initiated the creation of multiple algorithms aimed at predicting undesirable clinical outcomes, including mortality (Heyman et al., 2021) and readmission (Ashfaq et al., 2019). Subsequent to verifying the predictive efficacy of these algorithms, efforts began to integrate them into clinical practice to facilitate decision-making.

One model (and the specific unit of analysis in this study) focused on predicting mortality risk within 30 days post-discharge from the ED. This algorithm was endorsed by hospital clinical management for implementation in two EDs serving the region's 325,000 inhabitants. These EDs accommodate approximately 200 hospital beds and manage around 40,000 emergency department visits annually. The algorithm's purpose was to mitigate the uncertainties often associated with assessing and predicting the likelihood of patient mortality, which frequently leads to unnecessary interventions and treatments (Kennedy et al., 2014). The algorithm was structured as a clinical decision-support tool, operating as an alert system to signal elevated mortality risk. In practice, when a patient arrives at the ED, the algorithm analyzes their data in real-time, evaluating various clinical indicators and historical information. If the algorithm identifies a high mortality risk, it triggers an alert for the attending EP. This alert prompts the physician to undertake several specific actions. Firstly, the physician would conduct a thorough review of the patient's current condition and medical history, aided by the algorithm's findings. If the elevated risk is confirmed, the physician may refer the patient to their general practitioner for further evaluation and long-term management. Additionally, the physician might initiate discussions with the patient and their family about palliative care options or end-of-life planning, ensuring that the patient's wishes and comfort are prioritized. For instance, in a scenario where an elderly patient with multiple chronic conditions presents to the ED with severe respiratory distress, the algorithm might flag a high risk of mortality. The EP, alerted by the system, would then not only treat the immediate symptoms but also consider the broader context of the patient's overall health. This could lead to a decision to reduce aggressive treatments that may not significantly improve the patient's quality of life, focusing instead on symptom management and comfort care. This approach promised benefits both for patients and physicians. Patients would avoid needless discomfort by minimizing time spent in the ED and reducing unnecessary procedures. Physicians, on the other hand, would gain improved accuracy in assessing mortality risks, enabling better resource allocation and prioritization of treatment for patients with acute and urgent conditions.

During algorithm development, some ED management and operational personnel were deeply engaged in the research and development process, while others remained relatively unaware of the project's specifics. Varied levels of knowledge existed among ED managers and clinicians regarding the region's investments in data infrastructure and AI algorithm development. This ranged from extensive involvement in research and development, to limited understanding of the potential long-term impact on clinical practice. In the implementation phase, it was essential to gauge healthcare professionals' perceptions of the AI algorithm and to gather insights about its practical requirements.

### 3.2. Data collection

We collected data by conducting 18 in-depth interviews with healthcare professionals working at or with the ED. This is a figure within the norm for workplace studies and large enough to typically reach data saturation in qualitative research (Guest et al., 2020; Saunders and Townsend, 2016). Since the mortality algorithm was intended to be used by EPs, it is those we focus on in this paper. They are generally considered part of the dominant coalition at the ED (Hambrick and Mason, 1984). Emergency care is a medical specialty in Sweden, and it takes between 12 and 14 years to train as an EP. The education starts with a completed medical program at a university for five-and-a-half years, followed by a completed general service for at least 18 months to obtain a doctor's license, and ends with a specialization service for five-seven years. With the aim to interview healthcare professionals directly involved in the introduction and/or use of the AI algorithm, or those who would most likely be involved in the future, we recruited interviewees by using "purposeful sampling", where people are selected based on their knowledge and position (Patton, 1990). We also used a snowballing procedure, where one interviewee leads researchers to the next (Ekman, 2015). The final selection reflects the small number of experts at Swedish EDs and in Sweden with experience of AI algorithms. A total of approximately 25 specialists worked at the studied ED. We emphasized the voluntary nature of their participation and promised them anonymity. Ensuring anonymity and confidentiality meant we had to compromise on contextual details (Saunders et al., 2015); therefore, we could not provide specific information about the sample profile in terms of age, seniority, work experience, gender, ethnicity, and so forth. However, we ensured that the setting and sample profile were not entirely decontextualized by adding details regarding the research context and the interviewees' disciplines. Each interviewee was assigned a number in the order in which they are presented in the findings.

The interviews were semi-structured and open-ended to allow the interviewees to talk freely about their work. Informed consent was obtained from the participants. Owing to the COVID-19 pandemic, it was not possible to conduct face-to-face interviews, and we had to rely instead on online interviews using the Microsoft Teams software. The interviews lasted on average 1 h, were recorded, and then transcribed verbatim. Questions were broad and addressed, for example, the interviewees' current work situation (e.g., questions related to roles, responsibilities, tasks, challenges, and uncertainties), their views on and experiences of introducing and using new digital technology (e.g., AI in general and other healthcare technologies, but also especially linked to the mortality algorithm), challenges and opportunities related to daily work and the potential of AI to manage these, in particular the mortality algorithm, and the introduction of these technologies in practice (e.g., questions related to views on how the mortality algorithm works in clinical practice, and if and how it affects current work tasks and routines). All the interviews were conducted in Swedish, and to ensure fidelity with the original intent (Temple and Young, 2004), we retained native language words as far as possible during the research process.

### 3.3. Data analysis

We analyzed the data using an inductive three-step process inspired by that described in the literature (see Gioia et al., 2013), and which the data structure in Fig. 1 illustrates. The purpose of this was to get a deeper and more grounded sense of the meaning of the phenomenon, in our case how the introduction of new digital technology impacts uncertainty among physicians in clinical practice. In step one, we began by reading and re-reading the interview transcripts multiple times to get a good sense of the material. We used a line-by-line open coding process on the transcribed interviews, generating thick descriptions of the traditional work practices of physicians, and how these would alter following the introduction of an AI-based mortality algorithm. Open coding enabled us to code the common words, terms, and phrases used by the interviewees themselves, into first-order concepts. In step two, we searched for differences and similarities between the first-order concepts, and grouped them in relation to their focus, iterating back and forth between literature and the data. In this way, we were able to reduce the first-order concepts to second-order themes, clustered in relation to their focal point. For example, when examining these descriptions in detail, we noticed that they concerned ambiguity and uncertainty, which are aspects often discussed in medical sociological literature. For example, the physicians emphasized that one of the most imminent uncertainties in their traditional work is that linked to patient assessment, where it is difficult to determine how sick patients actually are, and their risk of dying. While physicians had learned to deal with this uncertainty, the new digital technology still offered them an appealing promise of additional novel and more precise information, largely helping them to make better and more certain assessments. However, as this technological possibility materialized, physicians simultaneously found themselves surrounded by, and triggered to learn to manage, three new forms of uncertainty brought by the new digital technology: epistemic uncertainty, actionable uncertainty, and ethical uncertainty. These forms emerged as analytically distinct and separated,

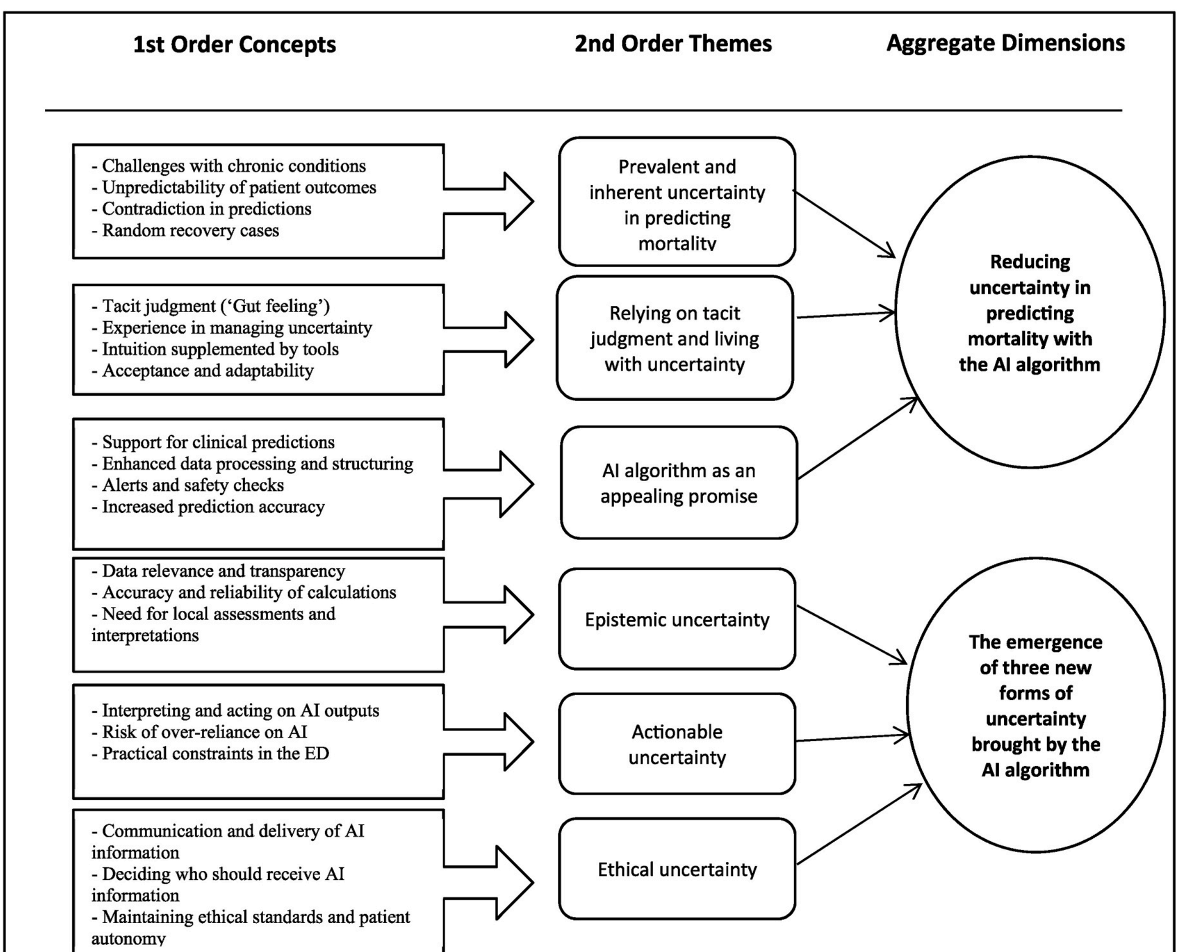


**Fig. 1.** Data structure.

in revealing and important ways, but at the same time are interrelated, as some degree of overlap in practice is possible. For example, in our analysis, the forms clearly differed in terms of their main essence: epistemic uncertainty was clearly linked to physicians' doubts in relation to the knowledge produced, trust, and explainability, while actionable uncertainty was clearly linked to their doubts in relation to usefulness and clinical utility, and ethical uncertainty to their doubts in relation to ethical and moral principles. At the same time, the new forms of uncertainty seemed to be connected temporally, as they could almost be understood as successive enactments: first, there seems to be uncertainty about how to understand the technology and trust what it generates, followed by uncertainty about how to act based on the technology's output, which is finally followed by uncertainty about the right way to act. With these insights, we focused on how the form and management of uncertainty started to be performed as a particularly revelatory change following the introduction of the new digital technology. In this we also traced the different instances of each form of uncertainty. In step three, and following our grounded analysis, we turned to the uncertainty literature and literature on the interplay between technology and uncertainty to help us make sense of our data and compare them with existing insights. Thus, after a more frequent iteration of going back and forth between data and literature, we were able to distill the second-order themes into two aggregate dimensions. In the following section, the findings are presented in line with our second-order themes and alongside the two aggregate dimensions.

## 4. Findings

### *4.1. Reducing uncertainty in predicting mortality with the AI algorithm*

One prevalent and important part of the overall uncertain situation at the ED is the difficulty for physicians to determine how sick a patient really is and the potential risk of them dying, often referred to as mortality prediction. This uncertainty was especially pronounced among certain groups of patients: "many patients who have chronic heart diseases, dementia, and so forth. could die in 30 days but many could also live two more years or even longer" (EP 07). Another physician highlighted the uncertainty and unpredictability: "they could quit tomorrow or in a year, no one knows. They are extremely difficult to assess" (EP 02). This uncertainty in predicting mortality was further elaborated on by a physician who described instances where their predictions were contradicted by patient outcomes:

> It's [predicting mortality] very difficult and uncertain. I have admitted patients who I have been absolutely certain will not live much longer. Have spoken to the relatives and all, and then a couple of days later the patient goes home in his usual state, which is not very good, but still. Vice versa also occurs but is probably not so common. (EP 08)

This highlights the inherent uncertainty in clinical judgment and the importance of understanding this aspect of emergency care. Further illustrating this point, another physician shared experiences with patient cases that challenged initial expectations:

> I've done that logical fallacy a few times, where you think this patient will die within 24 hours. They are so sick, there is no way they will survive. But then you still think that you should give it a chance and so you use all the medicines you have, and it goes as well as it can. And from being, as it were, completely at the absolute end of life, they recover and feel great and live another year or two. It happens. It's very fascinating and in my eyes completely random who makes it and who doesn't. (EP 04)

This illustrates the uncertainty but also emphasizes the complexity in making medical decisions in critical care situations. Given the uncertainty related to predicting mortality, deciding how to proceed was largely based on the physicians' situated tacit judgment, or what they often referred to as 'gut feeling'. This judgment was supplemented by information from other tools, e.g., blood samples and ultrasound images, at their immediate disposal:

> You always do a calculation in your head, but we don't have technical support for it. Instead, it's what we can call a feeling. Of course, it's based on a lot of facts but it's difficult to identify or describe. (EP 05)

This highlights the reliance on trained intuition and experience in the absence of concrete, technical support systems. Importantly, the physicians had largely become accustomed to living with the uncertainty and learned ways to manage it, rather than striving for strategies to eliminate or fundamentally control it: "We deal with this all the time, and we have learned to live with the uncertainty, but it takes quite a bit of experience" (EP 02). This emphasizes the adaptability and acceptance of healthcare professionals in the face of uncertain outcomes, largely relying on and trusting their extensive clinical experience. Even though the physicians had learned to live with and manage the uncertainty of predicting mortality, the introduction of an AI algorithm offered them an appealing promise to support their hunches with more precise tools: "[the AI algorithm provides] great clinical tools for these predictions" (EP 11), allowing them to draw on additional novel and more precise information. This understanding was echoed by another physician:

> We have a limited number of things we measure and with AI it's a goldmine of data, and precisely predicting [mortality] in a completely different way than we can and are able to do as humans. (EP 04)

This illustrates the potential of the AI algorithm to enhance predictive accuracy beyond human capabilities. Moreover, AI was seen more as a means to structure large amounts of data effectively:

> There is so much data everywhere that have to do with patients. There is information in various places and all the statistics and the calculations, but it's important to be able to produce it and use it for something positive in practice. It feels like there is a lot of information that could be useful, and AI helps us with that, and structures that information. (EP 06)

Together, these quotes highlight the role of the AI algorithm in organizing and making sense of complex data sets, thereby allowing physicians to overview and manage important information, and ultimately make their assessments with more certainty. As such, the AI algorithm was perceived to have the potential to not only produce more new and more precise information, but also to sort the information and, based on that, make more accurate predictions of mortality: "[predictions] are made better and more accurately by a computer" (EP 07). In addition, the AI algorithm was also perceived to have the potential to contribute to an increased sense of security in not missing anything critical, and to confirm and reinforce the assessment already arrived at by the physicians:

> The AI has the opportunity to give us a flag to watch out now, indicating that this is where things can go wrong. We get a flag to watch out, that this patient is sicker than you might think. You might not think this is a big deal but think again. It makes us ask if there is anything else it could be. A little red flag that comes up indicating wait now, watch out, don't proceed too fast. (EP 04)

> It can provide support and strength in what we have already arrived at. That we get security in our decisions and in being able to say that we don't do anything more because the [mortality] probability is so high. (EP 06)

Thus, the introduction of the AI algorithm in clinical settings was seen as a transformative tool that could address the inherent uncertainty in mortality prediction. By providing more precise data, structuring complex information, and offering a supportive role in clinical judgment, the AI algorithm had the potential to enhance the accuracy and confidence of physicians in making critical decisions.

### *4.2. The emergence of three new forms of uncertainty brought by the AI algorithm*

While the mortality algorithm had the potential to help physicians to reduce and manage uncertainty related to mortality prediction, it simultaneously brought three new forms of uncertainty in clinical practice: *epistemic uncertainty, actionable uncertainty,* and *ethical uncertainty* (see Fig. 2 for an overview of these). These were the result of unintended consequences emerging alongside the AI algorithm being introduced in practice, and required the physicians' deliberate and conscious control and management.

*Epistemic uncertainty.* The first emerging uncertainty was epistemic uncertainty, which involved ambiguity and doubts related to the knowledge generated by the technology, which was closely aligned with "trust in the information" (EP 01). We found three instances of this novel uncertainty. First, physicians were concerned about what data or information the AI algorithm was based on, and whether they could trust its relevance:

> I have a hard time understanding how the AI calculates, what parameters are included in the calculation of the risk of dying within 30 days … are concrete symptoms included? What data are included in this algorithm? (EP 06)

Another physician echoed this sentiment:

> It's interesting to know how the algorithm arrives at a specific number. Is it only epidemiological factors and previous illnesses, medications and such? Or does it consider the urgent here as well; what information is included? (EP 03)

With the uncertainty regarding which data are included and how relevant they are as a basis for the algorithm's calculations, physicians were triggered to ponder on and make sense of the data included in the AI algorithm. This required them to not only focus on diagnosing and treating patients but also to acquire data interpretation skills: "You have to think a lot and you have to know that the data you get are really relevant, too" (EP 03). Another physician highlighted this uncertainty and how it was managed:

> It alarms on my computer and shows that a patient has a high risk of dying and that I should check on them, but why does it say this? It can't be explained because the algorithm is not transparent. Are the variables patient-dependent or not? This creates a lot of uncertainty, and I have to go through everything then, and the patient's whole background. What is the patient's habitual state? What is the full background? (EP 12)

This new uncertainty required physicians to exercise deliberate and conscious control and management. They were not comfortable with it and made concerted efforts to reduce or eliminate it by thoroughly reviewing and understanding the data inputs and the patient's comprehensive background. This further highlights the added cognitive load on physicians to understand the underlying data driving the AI algorithm's recommendations and emphasizes the need for transparency and relevance in the AI algorithm's input.

Second, physicians expressed doubts about precision and accuracy in the calculations performed by the algorithm. They could not easily grasp how accurate the algorithm was, which contributed to an uncertainty as to whether or not they could trust its calculations and outputs:

> I don't know how, it's difficult for me to understand how accurate or reliable it is, e.g., whether it comes with 90% or 60% accuracy and regarding how much probability it indicates for a patient to die. How precise and accurate are these calculations? Such a high risk that a

| NEW FORMS OF UNCERTAINTY | | | |
|---|---|---|---|
| INSTANCES OF NEW UNCERTAINTY | EPISTEMIC UNCERTAINTY | ACTIONABLE UNCERTAINTY | ETHICAL UNCERTAINTY |
| | Instance 1: Uncertainty in relation to what data/information is included and its relevance. | Instance 1: Uncertainty in relation to how to act based on the algorithm's information and calculations. | Instance 1: Uncertainty in relation to delivering/communicatin g the results/information. |
| | Instance 2: Uncertainty in relation to the precision and accuracy of the algorithm's calculations. | Instance 2: Uncertainty in relation to the risk of not having acted and being able to act. | Instance 2: Uncertainty in relation to whether it should apply to all patients and always in all situations. |
| | Instance 3: Uncertainty in relation to the performance of the physicians' own assessments, which are required as the algorithm does not generate any absolute truth. | | |

**Fig. 2.** An overview of the three new forms of uncertainty brought by the AI algorithm.

> patent dies within 30 days … perhaps a 95% risk, then those are high numbers. (EP 07)

Another physician raised a similar concern:

> To what extent can I trust the information? If it says that a patient will die within 30 days, and it is 95% certain. Some patients may not even be suitable for this; there are some patients who are more difficult to make predictions about. Is the algorithm showing that these patients are difficult, that something extra comes up, e.g., a message that it is a weak prediction and explanation as to why? Why is it weak? 95% – how strong is that, really? (EP 13)

These quotes highlight specific clinical uncertainties regarding the AI algorithm's ability to produce reliable and accurate predictions in an ED setting. The uncertainty in understanding the accuracy of the algorithm, and how it applies to individual patient cases, creates a barrier to trust. The physicians were uncomfortable with this diagnostic uncertainty and took proactive steps to address it by critically evaluating the AI's predictions and cross-checking them with their own clinical judgments and patient backgrounds. The uncertainty related to precision and accuracy in calculations led the physicians to deliberately contemplate whether the algorithm "is right or wrong" and how "reliable it is". One physician commented: "It is required that we constantly think about how sure we are that it is correct." This ongoing reflection was crucial for them to mitigate the discomfort associated with this new uncertainty. They made concerted efforts to verify the AI algorithm's calculations through their expertise and experience. It was only after the physicians had thought over and become convinced of the precision and accuracy of the algorithm's calculations that they expressed they would go ahead and act based on them.

Third, even if the data or information on which the AI algorithm is based were completely transparent and relevant, and if the calculations were precise, the physicians still questioned the algorithm's ability to generate any absolute truth. Therefore, they felt that they would have to make local assessments and interpretations themselves to confirm or to further understand the prediction:

> An AI that says here we have something, I don't think it will ever be 100% true, so it's a risk if a flag becomes treated as a truth. It can be an additional tool, an additional help. (EP 05)

Another physician shared a similar view:

> It's a system that makes automatic interpretations, but we don't really trust it anyway, and always have to make our own interpretations as well. (EP 02)

How these local assessments and interpretations were to be performed was not evident or straightforward, but instead became subject to a high degree of uncertainty:

> It is for sure very difficult. Even if you were to get AI support there, it would still only be a matter of probabilities. I can't say with certainty that this patient won't live in a month, but we can say he/she probably won't. We may be able to predict what that probability is, but it's still likely we don't know for sure. (EP 09)

Another physician emphasized the need to remain attentive:

> You have to think a lot about the fact that just because they [the patients] are not marked with this, they can still be very sick. Although they don't fall out [in the algorithm], that's what you have to think about. (EP 05)

The reliance on and challenge of performing these local assessments and interpretations was further intensified by the unique environment of the ED, where rapid decision-making is crucial. One physician further emphasized the need for a cautious approach and the particularities of the ED:

> The algorithm is based only on probabilities, and every now and then, the unlikely happens, and you can end up in a very bad situation. Especially here in the ED where we have all different types of patients, the whole spectrum. So, it serves as a second opinion, but we must remain critical. (EP 10)

Thus, physicians need to maintain a critical perspective towards the AI algorithm's recommendations, acknowledging the inherent uncertainty and limitations of probabilistic models and the unique challenges of the ED environment. The quotes above highlight specific clinical uncertainties regarding the AI algorithm's role in the ED, where the dynamic and high-stakes nature of the environment demand not only accurate predictions but also clear communication of the limits of these predictions. Physicians addressed this uncertainty by carefully scrutinizing the predictions and using their clinical expertise to either validate or question the AI algorithm's outputs.

*Actionable uncertainty.* The second emerging uncertainty was actionable uncertainty; this involves ambiguity and doubts in relation to the actionability of the AI algorithm's output, which was closely aligned with clinical utility. We found two instances of this novel uncertainty. First, the physicians were concerned about how to act based on the information provided and the calculations made by the algorithm. They expressed uncertainty about interpreting the AI algorithm's predictions and incorporating them into clinical practice:

> There is a risk and uncertainty that we provide organizations and our people with information. The flow of information is extremely large today from various directions. It's important that I know what to do with that information. What I can sift through and what is important information. I need to know what to do with the information. (EP 01)

This highlights the added uncertainty of sifting through vast amounts of data to identify what is clinically relevant. Another physician elaborated on the need for clearer routines:

> It's also important that you know what you will do with that information. What will I do about this patient having an 80% risk of dying within 30 days? There should be perhaps even clearer routines than there are now. OK, what are you going to do? Maybe even so, if the AI says you have a 60% risk of mortality that this should be linked to some routine. Just so that it doesn't just become a number and then it becomes "yeah okay, what do I do with that number?" … So that it becomes something more concrete than, and doesn't just stop with, a number. (EP 13)

This points to the necessity of translating the AI algorithm-generated risk scores into actionable clinical guidelines. The need for practical guidance was echoed by another physician:

> How are you going to use this number in practice? How should you think? Because just a number doesn't lead to anything. What does this specific number imply I should do? Risk of mortality within 30 days according to AI, but this must also be linked to some kind of routine telling me what to do. Then something like this could pop up, "the patient has a 70% mortality risk, for more info see routine X". (EP 06)

As these quotations show, physicians were uncertain about how they should act based on the algorithm's information and calculations, and even wondered whether they should act specifically based on them or not. With this uncertainty, the importance was to transmit and mobilize data in ways to make them actionable; data that served the practical and clinical purposes of physicians: "I think it's difficult and unclear because you have to be very clear about what to do with the information" (EP 08). In this way, a single number did not provide the physicians with information that they considered to be actionable or useful. As the algorithm did not entail a specific routine or intervention, it was not providing a categorial answer, which triggered physicians to continuously reflect on what actions they considered appropriate.

Second, physicians expressed doubts and uncertainty about a risk of not having, or being able to act based on, the information provided and the calculations made by the algorithm:

> There is a risk that you become lazy and that you stop thinking for yourself. An uncertainty about not ending up with a clinical evaluation or assessment yourself. (EP 05)

Another physician added:

> One risk is that physicians lose their clinical competence. Because if part of decision-making is removed as it is done better by a computer that is more accurate, then it will become normal and we will not have to use our knowledge. We don't have to use our knowledge but just trust the computer … It will also then be difficult when you don't have AI there. (EP 07)

These quotes reflect a deeper uncertainty about how decisive the AI algorithm could become. Physicians expressed a risk of AI not just serving as a basis on which to act, but instead being afforded a key status in decision-making, which triggered reflection and doubt about whether it could render their clinical knowledge and judgment less important and perhaps even unnecessary. To manage this uncertainty, physicians remained careful about keeping their clinical evaluation skills and critical thinking, ensuring they did not become overly reliant on the AI algorithm output. In addition, they also expressed uncertainty about not being able to act based on the AI algorithm's predictions, given the practical constraints of the ED environment:

> If the goal is only to predict and do nothing more, then it doesn't matter, then we don't need to worry. But if the aim is that we should also do something for the benefit of the patient, then we have to make sure that we accept the responsibility and also ensure that there are the right resources. (EP 11)

Another physician stated:

> Using AI to predict someone's death in the emergency room, I see that as a bit problematic. Because of the way emergency departments look today, we don't really have the resources to act on and handle that information. (EP 08)

Further illustrating this uncertainty, another physician commented:

> We know that we will have to do the work of getting that patient admitted to a hospital other than our own, because we don't have time or places for them here, so you say, "Oh no, do I really have to take that patient, it's going to be so problematic". Then think how it will be: "Oh no, that patient has eight points on this AI", I need to start talking to the patient about life support and other measures. It will be very difficult to do all these things here, so there will be resistance. (EP 09)

This uncertainty and related practical challenges are intensified by the immediate and urgent focus inherent in emergency care:

> At the emergency department we are so incredibly focused on the here and now in some ways … You should go and run some tests for one patient and then you need to take a new blood sample from another one. So, you work a lot with what's here and now, what's purely current that has to do with the patient's current status. And in most cases, we don't pay a lot of attention to or put focus on what happens in the future, say within 30 days. (EP 10)

This highlights how the AI algorithm brings a tension between the core values and temporal structure of emergency care, which prioritizes immediate needs and excluding deadly diseases, versus the idea that physicians should also consider long-term care and end-of-life treatment for patients. To manage this actionable uncertainty, physicians generally projected the action based on the AI algorithm output to another place in the healthcare system, where they believed there was more time and resources, as well as medical specialties more familiar with the patient's overall condition, and a temporal orientation more aligned with prediction and planning for upcoming care:

> As an emergency physician, I'm responsible for the patient here and now at the emergency department … It's not like I'm responsible for planning their upcoming or future care. (EP 03)

Thus, even if they knew what to do and how to act, physicians questioned whether there was enough time and resources, both for themselves and in the wider healthcare system, to be able to handle and act on the information and calculations generated by the AI algorithm.

*Ethical uncertainty.* The third uncertainty to emerge was ethical uncertainty, involving ambiguity and doubts in relation to what conduct is "right" and "wrong", and which is closely aligned with ethical and moral principles. We found two instances of this novel uncertainty. First, physicians expressed doubts and uncertainty about how to deliver or communicate the information generated by the AI algorithm to patients:

> If the algorithm shows that this patient we have here actually has a high risk of not making it another month, then it leads to something else important; how should this be communicated. This is a really difficult thing … and it also requires quite a lot of experience and routine, as well as knowledge of communication. (EP 13)

This highlights the challenge of conveying potentially distressing information in a sensitive and comprehensible manner. Another physician elaborated on the difficulty of communicating the AI algorithm-based predictions:

> Now we have a system here in the emergency department that says you have a high risk of dying within 30 days, so now I'm going to discuss this with you. Somehow people get hung up on the fact that there is a system that says you will die within 30 days. We are different in how good we are at communicating things like this. (EP 11)

The impersonal nature of technology-mediated information can complicate communication, as it may be perceived as less human and more difficult to explain:

> Now when you get that alarm, how should you pedagogize this to the one who will receive it? It's easy for me, reasonably easy for me to say "this patient has had two major heart attacks, where he's been in for heart failure now five times in the last month. He's got this and that, and this debilitating disease, and then it is quite easy to present to the patient that here it is probably appropriate not to set the bar too high. But, if it has come from a machine, what and how should I say then? (EP 03)

These quotes illustrate the ethical dilemma of maintaining patient autonomy and providing clear, compassionate communication when delivering AI algorithm-generated information.

As AI algorithm-mediated information was perceived as more foreign and less easily explained, physicians expressed uncertainty and hesitation regarding how to communicate and deliver such computer or machine-generated information. This challenged their ethical principle of autonomy, and the duty to counsel and explain to a patient the diagnosis and treatment options.

Second, physicians expressed uncertainty and discomfort regarding whether the AI algorithm should be used for all patients or only a specific group of patients, and whether it should always be incorporated in all situations:

> There are a lot of ethical considerations around this. When you get this information, what are the patients' reactions and what should we do anyway? Should we talk to all the patients then and tell them their score? Is it ethically right, and is it ethical not to disclose it? Should everyone who visits the emergency department receive a little leaflet when they enter the waiting room or are picked up in the ambulance that reads, "now when you come to the emergency

department an AI will calculate whether you are at any risk of dying in the next 30 days. You will be given the result if you don't tick this box". (EP 04)

Another physician added:

I think a lot of people don't want to know that. And if I then find out about it, and have that knowledge, how should I handle it, if the patient totally refuses. Should I pretend that I didn't hear this and don't care about it or what? (EP 14)

This reflects the ethical dilemma of respecting patient autonomy while ensuring they are adequately informed, further complicated by the question of whether patients should always be informed about their AI-generated mortality risk:

But it's difficult because then you have to limit which patients are eligible for this kind of scoring. After all, you can't calculate this for everyone, and somehow it also has to be voluntary for the patient. They need to be asked. (EP 08)

One physician elaborated on the complexity of deciding who should receive the AI algorithm-generated scores:

It's a very difficult ethical question. Especially in those cases where you might not quite figure out why this patient gets an eight score. So, you see the numbers and the patient, but the patient might be seeking care for something very banal. But you still get these numbers as some vital parameter and co-morbidity emerges. Should you have to talk to this patient about a perhaps imminent death that an AI system has generated? It gets very, very strange, and if you choose not to do it, then you must also have some way to justify it. Why don't you bring this up, if the patient now has a high probability of dying? And as a patient, do you want to know that? Some certainly do want it, others absolutely not, and relatives and patients definitely don't think the same. It will be very difficult. (EP 09)

As these quotations show, there was not only uncertainty but also variation in how the physicians considered whether or not all patients should be subject to the AI algorithm. There was also uncertainty regarding the obligation to always share the AI algorithm-generated information or not. These together gave rise to intrusive and intense ethical and moral reflections, and physicians indicated the importance of developing ethical sensitivity: "there is a lot of ethical stance involved in that as well. It is very much about ethics" (EP 03). To manage this ethical uncertainty, physicians generally advocated for the creation of ethical forums, where such complex issues could be discussed and guidelines developed:

It's ethically difficult and I think some kind of ethical forum is needed to be able to discuss things like this, because the whole thing becomes a bit like science fiction. (EP 14)

It was believed that such forums would help ensure that the AI algorithm-generated information was communicated in a way that respects patient autonomy and maintains ethical standards.

## 5. Discussion

This study set out to answer the question: *How is the experience and management of uncertainty in clinical work affected by the introduction of AI in practice?* Our findings show that the introduction of an AI algorithm and its intended use reconfigured uncertainty among physicians at the ED. It was influential in reducing the profound and significant uncertainty emergency physicians experienced when predicting mortality. Their reliance on gut feeling and situated tacit judgment could now be supported and complemented by the 'hard facts' generated by AI. Importantly, however, our study, similar to other studies of the introduction of new digital technology in healthcare, as well as in the broader high uncertainty task contexts such as autonomous driving (see e.g., Constantinides et al., 2024; Timmermans and Angell, 2001; Timmermans and Berg, 2003; Timmermans and Buchbinder, 2013), showed that the consequences of the AI algorithm were multiple and contradictory in practice. This reflects the broader challenges noted by Berente et al. (2021), where AI's particularities can lead to unanticipated and contradictory outcomes, necessitating new approaches to manage these complexities. More specifically, our analysis highlights that while the mortality algorithm had the potential to help physicians to reduce and manage targeted uncertainty, it simultaneously brought three new forms of uncertainty into clinical practice: epistemic uncertainty, actionable uncertainty, and ethical uncertainty. While the physicians had learned to manage and live, and thus broadly developed comfort, with uncertainty (Bochatay and Bajwa, 2020; Fox, 1957, 1980, 2000; Ilgen et al., 2019), the new forms of uncertainty brought by the AI instead required their deliberate management and control (Atkinson, 1984; Light, 1979). This finding is particularly relevant in the context of algorithm aversion, a concept explored by Constantinides et al. (2024), who demonstrated that in high-uncertainty contexts like autonomous driving, users often struggle with the perceived limitations of AI systems, leading them to intervene and assert control rather than trust the AI completely. This highlights a broader pattern observed across different domains, where the introduction of AI can lead to a reassertion of human control in the face of uncertainty. In showing this, we make three main contributions to theory.

First, we contribute by advancing understanding of the recursive nature and temporal dynamics of uncertainty in medical work. Previous work has argued that while some forms of uncertainty may be addressed, new uncertainties often emerge in unanticipated places and situations (Fox, 1980; Timmermans and Buchbinder, 2013). In addition to confirming that uncertainty was reduced in one form while other new forms emerged, we extend this literature further by exploring in-depth how this recursive nature of uncertainty unfolds in practice. We specifically illustrate and conceptualize the new uncertainties that emerge when trying to manage an existing uncertainty, categorizing them into three distinct yet interrelated forms: epistemic, actionable, and ethical. In addition, we propose that these new forms of uncertainty are temporally entangled, enacted successively by physicians. Initially, physicians grapple with technological performance and trust in the AI-generated information (epistemic uncertainty). Next, they face uncertainty regarding how to act based on the AI's output (actionable uncertainty). Finally, they confront ethical dilemmas about the right way to act (ethical uncertainty). This fine-grained description of the recursive and temporal dynamics of uncertainty provides a grounded understanding of how uncertainty evolves in clinical practice (Diamond-Brown, 2016; Mackintosh and Armstrong, 2020; Timmermans and Berg, 2003).

Second, we contribute to theory by advancing understanding of attitudes towards and management of uncertainty in medical work. More specifically, while previous research has shown that physicians develop different attitudes towards uncertainty (Bochatay and Bajwa, 2020; Atkinson, 1984), our study highlights that these attitudes can vary depending on the *different forms of uncertainty*, which in turn has consequences for how uncertainty is managed. Prior to the introduction of AI technology, physicians had developed a comfort with the uncertainty related to mortality prediction through accumulated experience and tacit knowledge, enabling them to manage it reflexively. In this way, they could continue to and repeatedly experience uncertainty without necessarily being uncertain (see Timmermans and Angell, 2001, for a similar discussion). In contrast, the new forms of uncertainty introduced by the AI algorithm required a more deliberate and controlled approach. This shift illustrates a transition in how uncertainty is experienced and managed—from being mainly dealt with reflexively, as argued by Fox (1957, 1980), to being predominantly controlled through dominance, as suggested by Atkinson (1984) and Light (1979). Our findings challenge the binary view that physicians either seek to control uncertainty or acknowledge and deal with it reflexively, suggesting that both approaches are possible depending on the form of uncertainty. This insight aligns with and extends the argument provided by Constantinides et al. (2024), who discuss how individuals with varying levels of tolerance towards uncertainty interact differently with AI systems, such as in the context of autonomous driving. They acknowledge that individuals with low uncertainty tolerance tend to intervene more frequently, while those with higher tolerance might rely more heavily on AI. However, our findings suggest that uncertainty tolerance is not entirely fixed but can be dynamic and context dependent. In the medical setting, physicians may shift between controlling uncertainty and accepting it reflexively, depending on the specific nature of the uncertainty they face and the context of its occurrence. This indicates that while baseline uncertainty tolerance levels play a role, they can be influenced and modified by situational factors and the evolving interaction with AI. Taken together, this responds to calls for more in-depth accounts of how physicians experience uncertainty in clinical settings (Diamond-Brown, 2016; Mackintosh and Armstrong, 2020).

Third, our analysis advances the theoretical understanding of digital technology's role in managing medical uncertainty (Diamond-Brown, 2016; Mackintosh and Armstrong, 2020; Timmermans and Berg, 2003), with a specific focus on AI as an epistemic technology (Anthony, 2018; Knorr-Cetina, 1999). Our findings indicate that while AI in emergency care helps physicians reduce targeted uncertainties, it also introduces three new forms of uncertainty into clinical practice (Timmermans and Buchbinder, 2013; Bourret, 2005; Bourret and Cambrosio, 2019). These new uncertainties underscore the complex interplay between technology and practice, revealing how the integration of knowledge-producing technologies can both clarify and complicate clinical decision-making. More specifically, our study confirms that AI, by generating an abundance of information, not only reduces some uncertainties but also creates new challenges that are intertwined with technology and require innovative management strategies (Fox, 1980; Pilnick and Zayts, 2014; Timmermans and Angell, 2001). As physicians transition from traditional comfort with uncertainty in mortality prediction to a deliberate management of AI-induced uncertainties, our research highlights the need for new approaches to manage the overflow—characterized by an excess of information, choices, and responsibilities (Czarniawska and Löfgren, 2012). This shift points to a broader societal challenge, where the proliferation of information can lead to paradoxical increases in uncertainty, necessitating the development of new management strategies to effectively address the complex and evolving challenges introduced by AI technologies (see Berente et al., 2021).

In addition, we extend this literature by linking technology to attitudes towards uncertainty. As AI is often associated with generating more objective and rigorous knowledge, it brings expectations of providing unequivocal truth (Chen and Decary, 2020; Han et al., 2011; Pianykh et al., 2020; Topol, 2019). However, when these expectations are not fulfilled or become riddled with new forms of uncertainty, control and action are required. This relates to the concept of algorithm aversion discussed by Constantinides et al. (2024), where users tend to favor human judgment over AI in tasks perceived as highly uncertain or with significant consequences if errors occur. Physicians in our study showed similar behavior, revealing a reluctance to fully rely on AI-generated outputs. Our findings suggest that digital technology-mediated uncertainty is less likely to be accepted, or comfort with it to develop, than uncertainty stemming from physicians' medical knowledge. Thus, by drawing on a sociological perspective, we emphasize the importance of considering the socially embedded practices, assumptions, values, and beliefs that accompany new digital technology. This point aligns with the findings of Berente et al. (2021), who argue that the social dimensions of AI, including how users interact with and trust these systems, are as critical as the technical aspects. Previous research has largely focused on technological aspects and the importance of successful implementation (Gama et al., 2022; Petersson et al., 2022). While these aspects relate to epistemic uncertainty brought by the new AI algorithm, actionable and ethical uncertainties—despite being argued to cut across all facets of AI (Berente et al., 2021)—remain under-represented in empirical studies.

Our findings have important practical implications. As more novel technologies are developed and introduced into medical practice, it is crucial to approach the expectations and hopes attributed to them with a critical mindset. While these technologies promise to produce objective and accurate knowledge, and generate more certainty for physicians, our study highlights the importance of recognizing unintended consequences, such as how uncertainty can manifest in new forms that require new management strategies. Understanding that uncertainty is reconfigured rather than eliminated can make technology-mediated information and data more relevant and less dramatic for healthcare professionals. Introducing new digital technology to help manage uncertainty is a balancing act and a trade-off. Practitioners must understand that realizing the potential of new knowledge-producing technologies is closely connected with changes in other aspects of their work and should reflect on the flexibility and willingness required for these changes. This emphasis may also contribute to creating a constructive forum where healthcare professionals, technology developers, designers, and others can discuss both the intended and actual effects of the technology. By incorporating a sociological understanding of medical work, we can better equip ourselves to build healthcare technologies and systems that are sensitive to the social situations in which they are introduced and used.

While this study provides valuable insights, it also has certain limitations that offer avenues for future research. We adopted a single case study, something which limits the opportunities for generalizability. While our in-depth interviews allowed as to obtain a rich and contextual understanding of how new digital technology impacts uncertainty among physicians in emergency clinical practice, caution should be applied if and when attempts are made to transfer our conclusions to other contexts. We thus encourage future research to take our insights further and study the interplay between digital technology and uncertainty in other contexts. In addition to this more general caveat, there are also more specific limitations. First, our focus on a technology just recently introduced rather than on a taken-for-granted technology can be seen as both a strength and a limitation: it is a strength in that activities around it were not routinized but instead consisted of negotiations and controversies, which required the actors to express the reasoning behind their thinking and acting, and a weakness in that it was not possible to fully follow the new technology and related uncertainty for a significant period of time once it had come into use. Perhaps it may be that uncertainty is more prevalent in the introduction phase of a new digital technology than when it has actually become an integral part of practice. Thus, future research could focus on a time period not so close to the introduction of a new digital technology in order to advance understanding of how uncertainty unfolds over time and in relation to user experience and practices being well-established. Second, we have focused on the emergency care context, which is generally described as being centered on technological advancements, swiftness and variation. It may be the case that in other parts of a hospital or healthcare system, uncertainty and the interplay with digital technology is unfolding differently, and we would thus urge future research to advance our understanding in this regard. Third, while the main focus of the study and the interview questions was on the specific AI algorithm, we allowed interviewees to freely share their experiences of AI. This approach provided a broader context and understanding but may have occasionally led to discussions about AI in general. This openness is also a strength, as it allows interviewees to speak freely about their work, providing insights that are not constrained by predetermined problems defined by researchers. Future research could, however, address this by maintaining a stricter focus on the specific technology being investigated to ensure more targeted data collection and analysis.

Finally, due to the small size of the ED and the limited number of physicians, providing detailed information on demographics or work experience could compromise anonymity (Saunders et al., 2015). As a result, we could not account for the potential impact of varied experiences with the AI algorithm on the participants' experiences and management of uncertainty. Future studies could therefore benefit from a more detailed examination of the relationship between the length and frequency of AI usage, seniority, and the impact of these factors on experiencing and managing clinical uncertainty.

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## Ethic statement

The study adheres to the principles outlined in the Declaration of Helsinki and fulfilled the following research requirements: information, consent, confidentiality, and participant safety. Ethical approval for the research was not formally required under Swedish law, as no personal or sensitive information was handled. Each participant received written information encompassing the study's objectives and inception, outlining their role in the study, clarifying the collection of exclusively anonymous data, and delineating the methods for data collection and storage. They were also informed about the voluntary nature of participation, confidentiality, and the option to withdraw their consent at any point, without the need for justification.

## CRediT authorship contribution statement

**Daniel Tyskbo:** Writing – review & editing, Writing – original draft, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Conceptualization. **Jens Nygren:** Writing – review & editing, Project administration, Funding acquisition, Formal analysis, Methodology.

## Declaration of competing interest

We have no conflict of interest to declare.

## Data availability

Due to the nature of this research, participants of this study did not agree for their data to be shared publicly, so supporting data is not available.

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