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Artificial intelligence in trauma and emergency surgery: A quantitative study of perceived technology acceptance

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ABSTRACT

Artificial Intelligence (AI) is a transformative technology capable of driving the United Nations Sustainable Development Goals (SDGs) implementation across various industries. It can play a crucial role in the healthcare sector, especially in highly specialized fields such as trauma and emergency surgery, where its potential to assist in clinical decision-making is gaining widespread recognition. When appropriately designed and governed, AI applications in surgery can contribute to SDG 3 by improving health outcomes and promoting well-being. Moreover, clearly defined accountability and responsibility frameworks for AI in healthcare support SDG 16 by enabling auditability, clarifying responsibility allocation, and fostering institutional trust through transparent governance mechanisms. Despite these opportunities, ethical and governance-related concerns remain central to AI adoption and significantly shape the attitudes of medical professionals, patients, technology providers, developers, and policymakers. This exploratory study investigates surgeons' perceptions regarding AI adoption through a framework informed by the Unified Theory of Acceptance and Use of Technology (UTAUT). While grounded in UTAUT, the study incorporates context-specific constructs that capture the unique challenges of surgical practice: performance expectancy, perceived diagnostic complexity, patient-centered communication orientation, responsible AI governance climate, and shared accountability perceptions. By examining how responsibility interacts with traditional UTAUT constructs, performance expectancy, effort expectancy, social influence, and facilitating conditions, this research offers a more context-sensitive understanding of AI adoption in high-stakes medical environments. Through a comprehensive survey endorsed by the World Society of Emergency Surgery (WSES), involving 624 physicians from 72 countries, we aim to highlight these concerns and propose a conceptual model that reconciles AI's technological advances with the ethical obligations to protect patients and ensure sustainable healthcare outcomes.

1. Introduction

Artificial Intelligence (AI) is a disruptive technology that can support the implementation of the United Nations Sustainable Development Goals (SDGs) (United Nations, 2015) in multiple industries (Appio et al., 2023; Makridakis, 2017; Oppioli et al., 2023; Rajpurkar et al., 2022). Integrating AI and sustainable development can enable industries to shape a more sustainable world, meeting today's demands without compromising the well-being of future generations in the face of climate change and other critical challenges (Khakurel et al., 2018; Nishant

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et al., 2020). Within the Sustainable Development Goals framework, healthcare represents a foundational pillar (Dal Mas, 2024), with SDG 3 explicitly focused on ensuring healthy lives and promoting well-being across all age groups. The integration of AI[1] in healthcare also contributes to SDG Goal #16, as it promotes transparency, accountability, and institutional trust through responsible AI governance frameworks. Specifically, well-designed AI governance frameworks establish accountability regimes that clarify responsibility distribution among stakeholders, enable auditability of AI-assisted clinical decisions through transparent algorithms and documentation, support due process in clinical decision support by ensuring patients understand how their care is influenced by AI, and build institutional trust through clear lines of responsibility when adverse events occur.

AI-empowered applications are becoming increasingly popular in the healthcare and medicine domains (Basile et al., 2023; Dal Mas et al., 2023; Dicuonzo et al., 2022). AI represents a challenging yet valuable research topic in biomedical studies. In recent years, the quantity of AI-related studies has increased exponentially, with over 38,500 publications ranked on Pubmed in 2024 alone. While in 2014, only one AI-based application had the approval of the U.S. Food and Drug Administration for clinical use, namely, the AliveCor algorithm for the early detection of atrial fibrillation, in 2020, just before the COVID-19 pandemic, the number of approved AI-based algorithms in Europe was 240 (Conformite Europeene– CE-marked), while 222 were present in the United States (Muehlematter et al., 2021).

The majority of the literature agrees on how AI can contribute to better health outcomes by supporting clinicians in augmenting clinical decision-making processes (Basile et al., 2023; Loftus et al., 2020) with more precise diagnoses, predictions (Secinaro et al., 2021), and clinical risk management (Bertsimas et al., 2018). While several medical specialties are involved, significant applications include the detection of intracranial hemorrhages or vessel occlusions, stroke, traumatic brain injuries, acute findings in the abdomen, cancer diagnosis using computed tomography and magnetic resonance imaging scan, X-ray wrist fracture, the prediction of surgical risks and infections (Bertsimas et al., 2018; Cobianchi et al., 2022; Mascagni et al., 2021). Some of such applications can be extremely valuable in surgery, especially in challenging fields like trauma and emergency, where several factors (e.g. the patient's existing conditions or ongoing treatments, care preferences, and causes of trauma) can be unknown, and dynamics within the multidisciplinary clinical team members are of utmost importance to ensure effective patient care (Cobianchi et al., 2021; De Simone et al., 2021).

The opportunities brought by such a technology, and thus the potential contribution to SDG#3, seem underused. AI can process large volumes of patient data, facilitating quicker and more accurate diagnoses (Sulaieva et al., 2024). AI-supported decision-making in medicine can enhance the healthcare system's overall efficiency, thereby enabling improved quality, accessibility, and equity to medical services. The potential of AI is increasing the generation of healthcare data to improve patient care and reduce costs and clinical risks (Dal Mas et al., 2023; Dicuonzo et al., 2022). In decision-making, AI-driven diagnostics and treatment recommendations support clinicians, enabling more appropriate decisions and allowing healthcare workers to focus more on patient care while helping healthcare systems mitigate workforce shortages (Balch et al., 2021). This is crucial in achieving an adequate and well-distributed healthcare workforce globally, particularly in resource-limited settings (Boniol et al., 2022). By improving diagnostic accuracy, optimizing resource allocation, enabling proactive public health measures, and reducing health disparities, AI supports creating a more efficient, accessible, and equitable global healthcare system. AI in healthcare can help achieve the goal of all patients receiving fair and equitable care, regardless of their background, race, gender, socioeconomic status, or geographical origins. The application of AI enables innovations that help bridge gaps in care, accelerate progress in disease prevention and treatment, and advance the broader objective of ensuring healthy lives and well-being for all. This leads to better health outcomes and speeds up progress toward achieving sustainable, universal healthcare, which aligns with the objectives of the SDGs, particularly in promoting universal health coverage and equitable access to quality care (Dal Mas, 2024).

Despite the clear advantages of AI in supporting physicians' work, numerous studies across different medical fields have highlighted ethical constraints that may affect its acceptance and adoption (Cobianchi et al., 2022; Gundersen and Bærøe, 2022; Gupta et al., 2021; Russell et al., 2015; Vinuesa et al., 2020). As AI is not a neutral technology, recent studies show that AI can have a negative impact on people and the planet and, potentially undermining progress toward the SDGs (Gupta et al., 2021; Mancuso et al., 2025; Vinuesa et al., 2020; van Wynsberghe, 2021). Especially in the healthcare system, ethical issues may compromise the optimal use of AI-based applications, making it a liability rather than an asset. However, ethics in AI is a broad topic that goes far beyond the discipline of medicine (Figueroa-Armijos et al., 2022). Ensuring that AI is utilized in an ethical, fair, transparent, and responsible manner aligns with the goals of SDG #16, which emphasizes the promotion of peace, justice, and strong institutions. In the surgical context, unresolved ethical concerns, such as algorithmic bias, lack of transparency, and unclear liability, may hinder the trust and acceptance required for the effective integration of AI.

AI in medicine and surgery has been defined as the next frontier, and a valuable support tool for physicians in employing their job and guaranteeing effective care to patients (Cobianchi, Dal Mas and Ansaloni, 2022). While the number of AI-empowered medical tools is rising, exploring the knowledge and perceptions of its "dark side" by physicians still represents a research and practice gap that is worth investigating (Johnson-Mann et al., 2021; Loftus et al., 2023). Starting from these premises, this exploratory study aims to examine how surgeons' perceptions of AI influence their adoption intentions. Drawing on the principles of the Unified Theory of Acceptance and Use of Technology (UTAUT), we develop context-specific constructs that capture the unique aspects of AI adoption in surgical settings. Critically, we introduce shared accountability perceptions as a novel construct reflecting surgeons' beliefs about how responsibility should be distributed among surgeons, AI manufacturers, and data managers when AI tools contribute to clinical decisions.

Unlike perceived risk (which concerns expectations of negative outcomes), trust (which concerns belief in system reliability), perceived accountability (which focuses on personal attribution), or liability anxiety (which relates to fear of legal consequences), shared accountability perceptions capture normative beliefs about appropriate responsibility distribution. We argue that this construct shapes how surgeons evaluate other adoption factors and directly influences their willingness to adopt AI tools.

The research was conducted by enquiring a large international group of trauma and emergency surgeons to develop a conceptual model and propose practical solutions to overcome identified barriers. The field investigation was conducted with the endorsement of the leading international scientific society in trauma and emergency surgery, ensuring the study's relevance and credibility within the professional community.

The article is developed as follows. After a review of the current literature about technology acceptance dynamics in the adoption of AI-based tools, which enabled the design of the research hypothesis, a detailed methodological section reports how data was collected and analyzed. Results describe the outcomes of the field investigation, followed by a debate on the main findings and the possible contribution to

[1] It is important to clarify terminology. Machine learning (ML) is a subset of AI that enables systems to learn from data. This study addresses AI broadly while acknowledging that many surgical applications rely on ML techniques. Throughout this paper, 'AI' is used to encompass these technologies unless specific distinctions are warranted.

theory, practice, and policies. A conclusion paragraph highlighting the main limitations and recommendations ends the paper.

2. Literature review

2.1. AI in medicine and surgery

According to Secinaro et al. (2021), AI in healthcare can serve four main areas. The first is about offering potential support for comprehensive health services management. The second is for disease and outcome prediction, diagnosis treatment, and prognosis evaluation. The third is to support medical doctors and researchers in clinical decision-making by evaluating alternatives and their potential pros and cons. Last but not least, AI-based tools can help physicians deal with the vast amount of patient data to support diagnosis and treatments.

Surgeons face challenging clinical decisions while conducting an operation, mapping and forecasting risk factors, managing complications, and optimizing resource utilization (Loftus et al., 2020). Diagnostic and judgment errors represent the second leading cause of unnecessary surgical patient injury (Weprin et al., 2021). Therefore, surgical decision-making processes are dominated by hypothetical deductive reasoning and subjective judgment, both highly variable, potentially leading to errors that are hard to correct (Shanafelt et al., 2010). According to Loftus and colleagues (2020), surgical decision-making is subjected to four main challenges: the complexity of assessing all the potential diagnoses and their testing and eventual response to empirical treatments, the values and emotions and thus the possibility of engaging the patient in shared decision-making processes (Cobianchi et al., 2023), the time constraints and uncertainty, especially in trauma and emergency contexts, and the heuristics and bias, often leading to cognitive errors (O'sullivan and Schofield, 2018). In such a challenging context, AI can augment decision-making and help physicians reduce their biases, providing them with relevant information (Loftus et al., 2020). While the technical added value of some AI-based applications in surgery was proved (Loftus et al., 2022), a recent study has shown how the surgical community seems divided into two groups: those who are enthusiastic about AI application in their practice and those who have several concerns, preferring more traditional tools (Cobianchi et al., 2023). Differences in the enquired groups do not seem related to age (meaning, younger medical doctors belonging to Millennial and Generation Z versus senior colleagues), rather the role in the institution and the country of residence, highlighting a cultural aspect in the expectations and technology acceptance dynamics (Biancone et al., 2021; Venkatesh et al., 2016).

2.2. Technology adoption in high-stakes clinical work

Over the years, numerous theories and models have been developed to explain and predict technology acceptance and usage, reflecting the dynamic nature of technological advancements (Davis and Davis, 1989; Venkatesh et al., 2016; Venkatesh and Davis, 2000; Williams et al., 2015). Among these, the Technology Acceptance Model (TAM) (Davis and Davis, 1989), the Theory of Planned Behavior (TPB) (Ajzen, 1991), and the Innovation Diffusion Theory (IDT) (Nooteboom, 1994) have emerged as prominent frameworks. Building on these foundational approaches, the Unified Theory of Acceptance and Use of Technology (UTAUT), proposed by Venkatesh et al. (2003), has emerged as one of the most comprehensive and widely adopted models for analyzing technology adoption across diverse domains, including healthcare.

UTAUT encompasses four primary constructs, Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), and Facilitating Conditions (FC), which collectively influence Behavioral Intention (BI) to use a given technology. Performance Expectancy relates to users' beliefs about the benefits they will gain from using technology, while Effort Expectancy addresses the perceived ease of using it. Social Influence reflects the perceptions of important individuals in users' lives regarding the adoption of technology, and Facilitating Conditions pertain to the support and resources available to users for effective technology utilization (Venkatesh et al., 2003).

While UTAUT provides valuable theoretical grounding, Venkatesh et al. (2003), emphasized the need to adapt the framework for AI technologies, particularly given challenges related to autonomy and accountability. The surgical context presents additional complexities: decisions carry life-or-death consequences, multiple stakeholders contribute to outcomes, and legal-professional responsibilities are traditionally well-defined. Standard UTAUT operationalizations may not fully capture these domain-specific concerns. Accordingly, this study employs constructs informed by UTAUT principles but adapted to the surgical AI context. We retain performance expectancy as it aligns well with surgeons' outcome-oriented evaluations. However, we reframe the remaining constructs to reflect what our context-specific measures capture: perceived diagnostic complexity (rather than generic ease of use), patient-centered communication orientation (rather than peer/-institutional pressure), and responsible AI governance climate (rather than IT infrastructure and training). This approach allows honest reporting while maintaining theoretical grounding in technology acceptance research. Recent studies have applied adapted versions of the UTAUT to examine AI adoption in various fields, such as finance and accounting (Norzelan et al., 2024) and technology adoption among librarians (Akwang, 2021), demonstrating its versatility in analyzing technology acceptance across different domains, but also its versatility in terms of concept adaptation.

Following this premise we first tested the following variables and hypotheses.

Performance Expectancy (PE) - refers to the degree to which an individual believes that using a particular technology will enhance their job performance (Venkatesh et al., 2003). In the context of AI adoption among surgeons, studies have shown that the perception of AI as a tool that can improve patient outcomes and streamline workflows significantly influences their intention to adopt the technology (Loftus et al., 2021). Research has consistently identified performance expectancy as a critical determinant in technology adoption across various fields. For instance, Chua et al. (2018) and Gursoy et al. (2019) emphasize that when healthcare professionals perceive AI technologies as beneficial for improving service quality, their intention to adopt these technologies increases. Hazen B et al. (2014) further noted that high levels of AI competency and the perceived advantages associated with AI significantly enhance users' willingness to accept these tools. Moreover, Chen et al. (2019) highlighted that the relative advantages and compatibility of AI innovations play a vital role in determining their acceptance. In the meta-analysis of UTAUT constructs by Dwivedi et al. (2019), performance expectancy was identified as the most significant variable contributing to positive attitudes toward technology adoption. This underscores the necessity for healthcare practitioners, including surgeons, to perceive AI as an enabler of enhanced performance. Thus, we propose the following hypothesis.

H1. Performance expectancy positively influences the intention of surgeons to adopt AI technologies.

Perceived diagnostic complexity (PDC) captures the cognitive difficulty surgeons experience in clinical reasoning under uncertainty. Surgeons facing greater diagnostic complexity may be more receptive to AI decision support that helps manage this cognitive load. The construct was inspired by the UTAUT definition of perceived ease of use associated with technology (Venkatesh et al., 2003). The user-friendliness and intuitiveness of AI tools significantly impact surgeons' willingness to integrate these technologies into their practices. Research indicates a strong correlation between effort expectancy and technology adoption, affirming that user-friendly interfaces foster higher adoption rates (Pillai et al., 2024). The complexity of AI systems can present barriers to adoption; thus, if using AI requires significant effort, it may deter surgeons from embracing technology. Prior studies suggest that ease of use is a crucial determinant influencing users' acceptance of AI technologies (Gursoy et al., 2019). Furthermore, Oliveira et al. (2014) note that the easier technology is to integrate into existing workflows, the more likely it is to be accepted. However, challenges such as the immaturity of AI technologies and the lack of technical expertise can complicate the adoption process. Therefore, we propose the following hypothesis.

H2. Perceived diagnostic complexity positively impacts the behavioral intention of surgeons to adopt AI technologies.

Patient-centered communication orientation (PCO) reflects surgeons' commitment to involving patients in decision-making. Surgeons with strong patient communication orientations may value AI tools that enhance their ability to inform and engage patients, or might want to adopt tools that the pet. Derived from Social Influence (SI), this concept captures the extent to which individuals perceive that people important to them believe they should use a new technology (Venkatesh et al., 2003). In the surgical field, peers and leaders significantly impact technology adoption decisions. Surgeons are often influenced by the experiences and recommendations of their colleagues, with positive feedback enhancing the likelihood of adopting AI technologies (Melián-González et al., 2021). Research indicates that social norms and behaviors within professional communities play a critical role in shaping behavioral intentions. Gursoy et al. (2019) argue that societal pressures, particularly from younger professionals eager to adopt new technologies, can drive acceptance. According to social identity theory, the perceived support from one's social group regarding AI can enhance an individual's attitude toward its use (Gursoy et al., 2019). Moreover, studies have shown that social influence significantly contributes to positive behavioral intentions towards technology adoption (Baabdullah et al., 2022). Thus, understanding the dynamics of social influence is essential in the context of AI adoption among surgeons. Therefore, we propose the following hypothesis.

H3. Patient-centered communication orientation positively affects the behavioral intention of surgeons to adopt AI technologies.

AI governance climate captures surgeons' expectations regarding the ethical and regulatory infrastructure surrounding AI deployment, including data protection, transparency, and privacy. This variable acts as a f*acilitating Conditions (FC)* for performing a particular action as perceived by the user (Venkatesh et al., 2003). Ineed, for surgeons, the availability of organizational support, training, and technical infrastructure is crucial for the successful adoption of AI technologies. Research has shown that effective management support and adequate resources significantly influence the implementation of advanced technologies (Chong et al., 2009; Müller and Jugdev, 2012; Teo, 2006). Elbanna (2013) emphasizes that continuous managerial support is essential for project success, and a lack of such support can lead to project failure. Organizations that provide robust support systems can overcome barriers to technology adoption, thereby enhancing the perceived usefulness of AI (Loftus et al., 2021). Thus, facilitating conditions play a pivotal role in shaping surgeons' perceptions of AI technologies and their willingness to adopt them. Consequently, it is essential to recognize that better-facilitating conditions correlate with higher adoption rates of AI technologies. Therefore, we propose the following hypothesis.

H4. AI governance (AIG) positively influence the behavioral intention of surgeons to adopt AI technologies.

2.3. Responsibility and technology adoption in high-stakes clinical work

Responsibility is a well-known problem among technology adoption studies, and it directly addresses one of Venkatesh's key concerns: who is accountable when AI systems fail or behave unexpectedly? However, responsibility is a multifaceted construct and requires distinguishing it from adjacent constructs.

In this study, responsibility refers to surgeons' perceptions that accountability for AI-supported decisions is appropriately distributed, transparent, and institutionally actionable (e.g., who is answerable for adverse outcomes; what oversight is expected; and how accountability is operationalized across clinical, organizational, and technology stakeholders). This differs from trust, which concerns confidence in the AI system's competence and reliability; from perceived risk, which concerns expected probability/severity of harm; and from liability anxiety, which captures personal fear of legal consequences. Responsibility is also distinct from generic medico-legal risk aversion, which reflects broader professional caution independent of a specific technology. Responsibility works as a governance and role-clarity perception that shapes whether AI can be incorporated into clinical work without creating unacceptable accountability ambiguity. It operates as an antecedent rather than a moderator because it represents a foundational belief that develops prior to and shapes evaluations of specific technology attributes. When surgeons believe accountability should be appropriately shared among stakeholders, this baseline orientation influences their subsequent perceptions of performance benefits, communication requirements, and governance adequacy.

Moving from this premise, surgeons are more likely to adopt AI tools when they perceive that ethical, professional, and legal responsibility is well-distributed, transparent, and manageable (Holzinger et al., 2020; Jiang et al., 2017). If AI is perceived to shift the burden of responsibility in ambiguous or uncontrolled ways, e.g., in fully autonomous systems lacking human override options, behavioral intention to adopt such technologies tends to diminish (van Wynsberghe, 2015). As Venkatesh (2022) also noted, perceived loss of agency and accountability ambiguity can serve as a significant barrier to AI adoption, reinforcing the need for contextual extensions of the UTAUT model. Accordingly, we formulate the following hypothesis.

H5. Responsibility positively influences surgeons' behavioral intention to use AI tools.

Responsibility serves not only as a direct antecedent to behavioral intention but also as a construct that influences how core UTAUT dimensions, performance expectancy, effort expectancy, social influence, and facilitating conditions, translate into intention and actual use.

The literature consistently highlights that when surgeons retain control over AI systems, able to validate, override, or adjust AI recommendations, they perceive these technologies as more useful (Jiang et al., 2017). For instance, AI tools that propose surgical strategies requiring surgeon validation promote a collaborative environment where technology enhances human skills (Stanfill and Marc, 2019; Topol, 2019). Depending on the circumstances and the requirements, surgeons may capitalize on technology and integrate their skills with it. Recent AI-empowered surgical robots may exhibit a certain degree of autonomy (Panesar et al., 2019; De Simone et al., 2022). Indeed, they can propose strategies to be validated, carry out the decision-making process, achieve autonomy for specified tasks, or even be fully autonomous. The more autonomy is reached, the more ethical concerns may arise. In the future, surgical robots remotely controlled and empowered by AI could be used to perform operations in hostile environments, such as battlefields for wounded soldiers, lengthy flights, or onboard international space stations (Cobianchi et al., 2022). Dealing with AI-empowered surgical robots requires developing a different set of abilities, including non-technical skills, which should probably be different from those present in traditional surgical environments (Pradarelli et al., 2020). Nevertheless, technology lacks the soft-skill capabilities that distinguish surgical leaders (Calinon et al., 2014; Caputo et al., 2019). An effective human-machine collaboration ensures that the surgeon's autonomy and decision-making remain central, fostering trust in AI applications. Therefore, when responsibility is clearly shared, and human oversight is preserved, AI systems are more likely to be seen as useful and reliable. Responsibility enhances performance expectancy by clarifying oversight structures and preserving surgeon autonomy. Clear lines of accountability reduce uncertainty and enhance trust, thus increasing perceived usefulness, which is the core of performance expectancy in the UTAUT model. Therefore, we propose the following sub-hypotheses.

H6a. Responsibility positively influences performance expectancy.

H6b. Responsibility facilitates behavioral intention to use AI tools through the mediating effect of performance expectancy.

Moreover, AI systems designed with interfaces that allow for surgeon interaction and feedback further enhance perceived usefulness (Holzinger et al., 2020). Such systems enable surgeons to input their expertise, adjust AI parameters, and engage in a dynamic decision-making process, reinforcing the notion that AI is an extension of their capabilities. Conversely, fully autonomous AI systems that limit human intervention raise ethical concerns and can diminish perceived usefulness due to fears of loss of control and accountability (van Wynsberghe, 2015). Physicians may be hesitant to rely on AI that operates without the possibility of oversight, especially in high-stakes environments like emergency and trauma surgery. Systems that allow for human override and provide clear responsibility cues reduce perceived complexity and cognitive friction (Topol, 2019).

Systems that clearly communicate responsibility boundaries reduce cognitive load and ethical ambiguity. Intuitive interfaces and override capabilities reinforce surgeon control and lessen the perceived effort required to integrate AI into workflows (Holzinger et al., 2020). Thus, responsibility contributes to lowering friction in AI use. Therefore, we derive the following sub-hypotheses.

H7a. Responsibility positively influences the effort expectancy.

H7b. Responsibility facilitates behavioral intention to use AI tools through the mediating effect of effort expectancy.

Shared responsibility enhances human control by establishing a collaborative framework where both AI systems and surgeons contribute to decision-making. Clear guidelines on the extent of AI's autonomy and the surgeon's oversight responsibilities ensure that surgeons remain central to the process (Loftus et al., 2020; Yu et al., 2018). This collaboration promotes confidence in using AI, as surgeons understand how and when to rely on AI outputs. Furthermore, technical robustness supports shared responsibility by providing reliable AI outputs that surgeons can confidently incorporate into their practice (Rieke et al., 2020). The combination of robust technology and a shared responsibility model empowers surgeons to exercise control over AI systems effectively. Ethical norms and expectations around responsibility shape peer attitudes and institutional policies, influencing the social acceptability of AI (Yu et al., 2018). Thus, when shared responsibility is evident and ethically justified, peer support and organizational endorsement become more likely, strengthening social influence mechanisms. Therefore, we propose the following sub-hypotheses.

H8a. Responsibility positively influences social influence.

H8b. Responsibility facilitates behavioral intention to use AI tools through the mediating effect of social influence.

Institutional infrastructures that clearly define legal, ethical, and operational responsibilities play a critical role in facilitating the adoption of AI in surgical settings (Venkatesh, 2022). Given the complexity and high hazards of surgical procedures, AI systems must demonstrate technical robustness to ensure safety and build clinician trust. When AI performs reliably, surgeons are more likely to feel confident in maintaining control over its application (Esteva et al., 2019). In a continual learning framework, AI algorithms become more accurate and precise over time, *but only if they are trained on high-quality, representative, and appropriately annotated data*. Early versions of these systems, which may rely on incomplete or poorly curated datasets, risk offering suboptimal decision support to both surgeons and patients (Cobianchi et al., 2022). For example, using low-quality surgical videos, whether due to lack of expertise from the operating surgeon or inadequate annotation, can compromise model reliability and lead to adverse clinical outcomes (Madani et al., 2020; Mascagni et al., 2021). AI systems must be designed with transparency and explainability at their core to mitigate these risks and foster trust among clinicians, patients, and regulators. Explainable AI (XAI) approaches help clarify how AI systems reach their conclusions, making them more interpretable and accountable (Saeed and Omlin, 2023). Furthermore, the integration of cybersecurity technologies is essential to ensure data protection and system integrity, particularly when sensitive patient information is involved (Garcia-Perez et al., 2023). Equally important is the establishment of robust data governance frameworks. These ensure the quality, security, and ethical management of the data used to train and operate AI systems (Rieke et al., 2020). By defining stakeholder responsibilities in data handling, data governance directly contributes to the broader notion of shared responsibility (Floridi et al., 2018). Well-articulated policies around data stewardship, privacy compliance (e.g., GDPR), system transparency, cybersecurity, and institutional liability provide the necessary scaffolding for responsible AI deployment in clinical environments.

Taken together, these infrastructural components such as technical robustness, data governance, explainability, and cybersecurity form the backbone of enabling conditions that support the ethical and effective integration of AI in surgery. In this context, the construct of *responsibility* not only reinforces accountability but also enhances the facilitating conditions for AI adoption.

Therefore, we propose the following sub-hypotheses.

H9a. Responsibility positively influences the facilitating conditions.

H9b. Responsibility facilitates behavioral intention to use AI tools through the mediating effect of facilitating conditions.

The following Fig. 1 shows the hypothesis conceptual model.

3. Methodology

3.1. Design and setting

Data was collected using a population-based online questionnaire to gather demographic, knowledge, and practice-based information regarding the adoption of new technological tools, especially those AI-based, to support clinical decision-making. The initiative was endorsed and publicized by the World Society of Emergency Surgery (WSES) (World Society of Emergency Surgery, 2022), one of the major

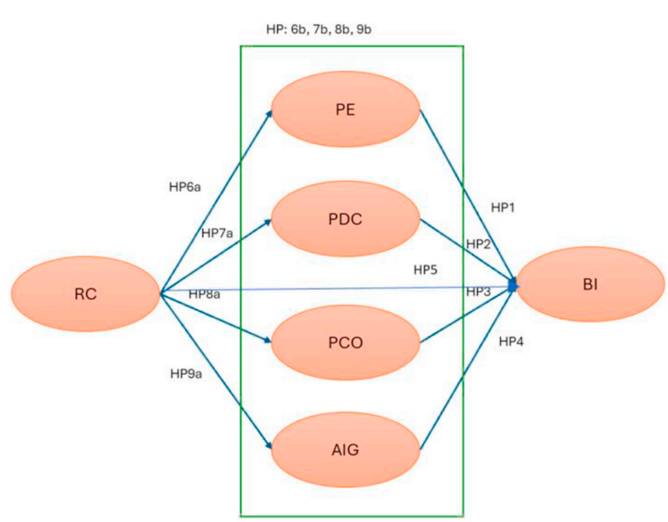

Fig. 1. Conceptual model.

scientific societies in the field. Given this dual recruitment approach, we cannot calculate a precise response rate, and therefore refrain from reporting one.

An initial research protocol was conceived and shared by the principal investigators, starting with a review of the literature. The complete protocol was peer-reviewed and published (Cobianchi et al., 2023). The leading references to create the protocol and the survey structure were gathered from Dal Mas et al. (2020), Loftus et al. (2020a, 2020b, 2020c), Cobianchi et al. (2022, 2022), Venkatesh et al. (2003, 2012, 2000), and Bashshur et al. (2011). A dedicated steering committee was formed within the WSES, comprising academics and practitioners in trauma and emergency medicine, healthcare management and policies, organization science, innovation, business and clinical ethics, information technology, and law. The WSES steering committee reviewed the online survey, which was filled in by a sample of physicians before its official launch. The full version of the questionnaire and preliminary results were published in the society's official journal after peer review (Cobianchi et al., 2023).

The online questionnaire was delivered through Google Forms, according to the Checklist for Reporting Results of Internet E-Surveys (CHERRIES) (Eysenbach, 2004). The initiative remained open between November 2021 and August 2022. The 917 WSES members received an e-mail invitation to participate in the survey. The invitation message included comprehensive details on the initiative's aims, underlying rationale, and the estimated duration (about 10 min). Moreover, the project was also shared on the society's website and Twitter/X account. Four e-mail reminders were sent. WSES membership was not requested. However, only medical doctors could participate. 650 physicians from 72 countries filled in the questionnaire. Given the advertising campaigns promoted by the WSES, it may be assumed that most participants belong to the 917 active members.

3.2. Survey

A preliminary set of questions aimed to gather general information on respondents (Table 1), such as personal and demographic data, and to measure the control variables. The questions' list was derived from previous WSES investigations (Cobianchi et al., 2021; Cobianchi et al., 2022), and they included gender, years of experience in surgery, type of institution (a university or research hospital or not), country of residence, role, eventual participation within a trauma team, the clinical specialty of the trauma leader, the attended educational training, and the eventual presence of diverse peers in the surgical equipe. From the initial 650 questionnaires, 26 were not taken into account due to the low number of responses from the continent. Therefore, only responses from Asia, Europe, South America, and North America were considered, totaling 624 questionnaires. Descriptive statistics related to these are reported in Table 1.

Table 1
Descriptive statistics of respondents.

Variable	Respondents
Type of Institution	
Belonging to an Academic Institution	476
Belonging to non Academic Institution	148
Gender	
Male	506
Female	117
Prefer not to answer	1
Experience	
Less than 15 years (excluded)	379
15 years and more	245
Continents	
Asia	90
Europe	474
North America	31
South America	29
Total	624

3.3. Measures

This study draws on the Unified Theory of Acceptance and Use of Technology (UTAUT) as its theoretical foundation while employing context-specific constructs adapted to the unique demands of surgical AI adoption. This approach aligns with established methodological guidance on theory application in specialized domains. For example, Venkatesh and colleagues, in their original UTAUT formulation, explicitly acknowledged that the model's constructs may require adaptation when applied to new technological and organizational contexts (Venkatesh et al., 2003). This flexibility is not a methodological weakness but rather a design feature of the framework, enabling researchers to capture domain-specific dynamics that generic operationalizations might miss. As Venkatesh (2022) later emphasized, the emergence of AI technologies introduces novel challenges, particularly regarding autonomy, opacity, and accountability, that call for theoretical extensions beyond traditional technology acceptance factors.

The methodological literature on scale development and adaptation supports context-sensitive measurement approaches. According to MacKenzie et al. (2011), construct validity depends not merely on replicating prior operationalizations but on ensuring that measures accurately capture the theoretical domain as it manifests in a given context. When the phenomenon of interest differs meaningfully across settings, as clinical AI adoption differs from, say, consumer technology adoption, faithful representation of the construct may require tailored items rather than direct replication.

In high-stakes clinical environments, technology adoption involves considerations that extend beyond generic usability and social pressure. Surgeons operate under conditions of diagnostic uncertainty, professional liability, patient communication obligations, and governance expectations that shape their technology perceptions in distinctive ways. Standard UTAUT items, developed primarily in organizational IT adoption contexts, may not adequately capture these domain-specific concerns.

3.4. Measure scale development and contextual adaptation procedure

Following established best practices for adapting existing theoretical frameworks to specialized domains, this study developed measurement items through a multi-stage, theory-informed, and practitioner-validated process. The objective was to preserve the conceptual integrity of UTAUT while ensuring that the operationalization accurately reflected the realities of AI-supported decision-making in surgical practice.

First, an initial pool of items was derived from prior validated scales in the technology acceptance and information systems literature. Wherever possible, established UTAUT measures were adapted through contextual rewording rather than replaced, in line with recommendations for theory-consistent scale adaptation. For constructs that are not explicitly captured in the original UTAUT framework, such as responsibility conditions and AI governance-related perceptions, items were developed deductively based on prior conceptual and empirical work on accountability, governance, and ethical responsibility in clinical AI.

Second, to ensure domain relevance and content validity, the preliminary set of items was reviewed in collaboration with experienced surgeons affiliated with the surgical scientific society that sponsored the questionnaire. These experts provided feedback on item clarity, clinical realism, and relevance to everyday surgical decision-making. This step ensured that the measures reflected not only theoretical expectations but also the target population's professional language and concerns.

Third, the revised questionnaire was administered to a small pilot sample of clinicians prior to the main data collection. The pilot study served to assess item comprehension, wording clarity, and response variability. Based on pilot feedback, minor refinements were made to improve readability and reduce ambiguity, while preserving the underlying theoretical meaning of each construct.

This multi-stage process is consistent with methodological guidance emphasizing that construct validity in applied research depends on both theoretical grounding and contextual appropriateness. By combining theory-driven item development with expert validation and pilot testing, the study ensures that the adapted measures faithfully represent the constructs of interest as they manifest in high-stakes surgical AI adoption contexts.

3.5. Likert scale questions

This study employed reflective, multi-item indicators and five-point Likert-type response formats for all multivariate constructs. Whenever feasible, validated items from previous studies were incorporated. For constructs lacking established measures, new items were developed in alignment with theoretical foundations and methodological guidance from existing literature. Items for each variable are reported in Table 2.

All the scales and items used in this study have been adapted from previous research (Davis and Davis, 1989; Dwivedi et al., 2021; Venkatesh et al., 2003, 2012; Venkatesh and Davis, 2000).

Table 2
Constructs and indicators of the study.

Construct	Indicators
PE	PE1: Machine learning and Artificial intelligence-based applications help in scouting and reviewing publications supporting clinical decision-making
	PE2: Machine learning and Artificial intelligence-based applications reduce the span of options and support clinical decision-making
	PE 3: Machine learning and Artificial intelligence-based applications support taking complex clinical decisions
	PE 4: Machine learning and Artificial intelligence-based applications help in evaluating/validating decisions I would take
PDC	PDC1: It is often too complicated to form a complete list of all likely diagnoses, all life-threatening diagnoses, and all unlikely diagnoses that may be considered if the initial workup excludes other causes
	PDC2: It is often too complicated to recognize the strengths and limitations of available tests
	PDC3: How would you rate the following statement: Data are often incomplete when I have to make decisions
PCO	PCO1: How would you rate the following statement: Understanding the patients preferences
	PCO2: How would you rate the following statement: Explaining to the patient that his/her opinion is important in making the decision
	PCO3: How would you rate the following statement: Giving information in more ways than only verbally (e.g., leaflet, website).
AIG	AIG1: Data should be managed carefully when used in Machine learning and Artificial intelligence-based tools
	AIG2: Patients should know how the decision was made when Machine learning and Artificial intelligence-based tools are used
	AIG3: Non-technical skills should be adapted and changed if new technologies like AI are involved
	AIG4: Preserving patients privacy is fundamental when Machine learning and Artificial intelligence-based tools are used
RC	RC1: How would you rate the following statement: Surgical responsibilities should be shared with the manufacturer of the technologies used in Machine learning and Artificial intelligence-based tools
	RC2: How would you rate the following statement: Surgical responsibilities should be shared with the data manager of Machine learning and Artificial intelligence-based tools
	RC3: How would you rate the following statement: Surgical responsibilities should be shared with those in charge of the maintenance of Machine learning and Artificial intelligence-based tools
BI	BI1: Machine learning and Artificial intelligence-based tools will be critical for clinical decision making in a five-year horizon
	BI2: Machine learning and Artificial intelligence-based tools are relevant for today clinical decision making
	BI3: Digital technologies (e.g. artificial intelligence) support how I take clinical decisions
	BI4: Machine learning and Artificial intelligence facilitate clinical decision making

Performance Expectancy (PE) reflects the degree to which users believe that machine learning (ML) and artificial intelligence (AI)-based applications improve their clinical decision-making performance. This construct was measured using four items adapted from Venkatesh et al. (2012), each capturing a specific perceived benefit of AI in the clinical context: supporting the review of relevant publications, aiding in complex clinical decision-making, and assisting in the evaluation or validation of clinical decisions, thereby enhancing users' confidence and accuracy in their decision-making (Davis and Davis, 1989; Venkatesh et al., 2003; Venkatesh and Davis, 2000).

Perceived Diagnostic Complexity (PDC) was measured as the perceived ease or difficulty clinicians experience when using available tools and information for clinical decision-making. It was assessed through three items capturing key diagnostic challenges: the complexity of forming a comprehensive list of potential diagnoses when initial tests are inconclusive; the difficulty in evaluating the strengths and limitations of diagnostic tests; and the challenge of making decisions with incomplete data, reflecting the cognitive effort required in real-world clinical settings (Davis and Davis, 1989; Venkatesh et al., 2003, 2012; Venkatesh and Davis, 2000).

Patient-Centered Communication Orientation (PCO) construct was operationalized using three items focused on patient-centered communication and shared decision-making in the context of AI-based healthcare technologies. These items measured the impact of patient values and expectations on clinicians' decision-making, highlighted the importance of involving patients in decisions, and assessed the expectation for effective and inclusive communication, all of which can affect the adoption and use of technology. The items were adopted from previous studies (e.g Venkatesh et al., 2003; Venkatesh, 2000).

AI Governance Climate (AIG) was operationalized by assessing individuals' perceptions of the availability and adequacy of technical and organizational infrastructure needed to support the effective use of machine learning and AI-based tools. İt was measured through 4 items that reflect the extent to which users believe that necessary resources, support systems, and compatibility are in place to enable smooth technology adoption and use (Venkatesh et al., 2003, 2012).

Following the working definition adopted in this study, Responsibility Conditions (RC) were assessed through items designed to capture perceptions of how accountability is shared among stakeholders involved in the use of AI in surgical settings (Byerly et al., 2021; Cobianchi et al., 2022; Venkatesh, 2022). Specifically, participants rated their agreement with statements regarding whether surgical responsibilities should be shared with the manufacturers of AI tools, the data managers overseeing these technologies, and those responsible for their maintenance.

Behavioral Intentions (BI) were operationalized by measuring the strength of individuals' intentions and willingness to use AI-based tools in clinical decision-making. Grounded in established theories of behavior, such as those by Ajzen and Fishbein, (1977), Davis and Davis (1989), and Venkatesh et al. (2003), BI was assessed through items that capture both the current and future relevance of these technologies. These items collectively reflect the respondents' commitment and readiness to adopt AI-driven tools in healthcare.

Each item likely used a Likert-type scale (e.g., from "strongly disagree" to "strongly agree") to gauge respondents' perceptions of the performance benefits provided by these technologies.

Countries. These are control variables in the model. We created a set of dummy variables, one for each continent. The selected countries were located in Asia, Europe, South America, and North America.

3.6. Data analysis

Partial Least Squares Structural Equation Modeling (PLS-SEM) was utilized in this study given its effectiveness in handling complex models and data that deviate from normality. As a variance-based SEM technique, PLS-SEM is widely adopted for estimating path models, particularly in exploratory research settings. It operates as a regression-based method aimed at minimizing the residual variance in endogenous variables (Hair et al., 2011). The approach follows an iterative algorithm that seeks to maximize the explained variance within the model constructs (Merli et al., 2019). Given that the dataset exhibited non-normal distribution, PLS-SEM was deemed appropriate, as it does not require normality assumptions (Hair et al., 2011). To assess the structural model and test the hypotheses, SmartPLS version 4.0 was employed. A bootstrapping procedure with 5000 resamples was conducted to estimate path coefficients and corresponding t-values, covering both direct and mediating effects.

4. Results

4.1. Evaluation of the outer measurement model

To establish the robustness of the measurement model, a thorough evaluation of its reliability and validity was conducted, following the guidelines proposed by Hair et al. (2011). Internal consistency was assessed using Cronbach's alpha and composite reliability, with both metrics exceeding the accepted threshold of 0.70, indicating satisfactory reliability across all constructs (see Table 3).

Convergent validity was evaluated through the Average Variance Extracted (AVE), with each construct demonstrating an AVE value above the recommended cutoff of 0.50, thereby confirming adequate convergence (Table 3). Discriminant validity was assessed using the Fornell-Larcker criterion (Table 4). As detailed in Table 4, the square root of each construct's AVE was greater than its correlations with other constructs, supporting discriminant validity. Also Table 5 shows the Heterotrait-monotrait ratio (HTMT) – Matrix.

Given the reliance on self-reported data, additional steps were taken to mitigate the risk of common method bias. Harman's single-factor test was performed, and the results showed that the first factor accounted for less than 50% of the total variance, suggesting that common method variance is not a major concern. Further, inspection of the correlation matrix revealed no coefficients exceeding 0.900, offering additional assurance.

Model fit was assessed using the Standardized Root Mean Square Residual (SRMR), which yielded a value of 0.071—below the threshold of 0.080—indicating an acceptable fit for the measurement model. Additional model fit indicators are provided in Table 6. Moreover, all Variance Inflation Factor (VIF) (Table 7) values were within acceptable limits, alleviating concerns about multicollinearity. Finally, Table 8 shows the outer loading and Table 9 the.

These results collectively affirm the measurement model's reliability and validity, providing a solid foundation for subsequent hypothesis testing.

4.2. Assessment of the structural inner model

As previously mentioned, the structural model was assessed using PLS-SEM to test the hypothesized relationships. Results confirm the model's robustness and underscore the critical importance of ethical and professional accountability in influencing BI to adopt AI tools among surgeons.

Table 3
Construct reliability and validity.

Variable	Cronbach's alpha	Composite reliability (rho_c)	Average variance extracted (AVE)
BI	0.759	0.847	0.581
EE	0.759	0.861	0.678
FC	0.731	0.820	0.532
PE	0.831	0.888	0.667
RC	0.934	0.958	0.884
SI	0.732	0.803	0.585

Table 4
Fornell-Larcker criterion.

	BI	PDC	AIG	PE	RC	PCO
BI	0.762					
PDC	0.220	0.823				
AIG	0.401	0.078	0.730			
PE	0.692	0.220	0.480	0.817		
RC	0.289	0.273	0.233	0.276	0.940	
PCO	0.264	0.079	0.323	0.239	0.158	0.765

Table 5
Heterotrait-monotrait ratio (HTMT) - Matrix.

	BI	PDC	AIG	PE	RC	PCO
BI						
PDC	0.293					
AIG	0.472	0.145				
PE	0.862	0.284	0.578			
RC	0.342	0.311	0.258	0.314		
PCO	0.274	0.139	0.489	0.277	0.112	

Table 6
Model fits.

Model fit measures	Value
SRMR	0.071
d_ULS	1.657
d_G	0.465
Chi-square	1876.400
NFI	0.762

Table 7
VIF.

	VIF
AIG1	1.745
AIG2	1.538
AIG3	1.114
AIG4	1.682
PCO1	1.513
PCO2	1.744
PCO3	1.339
RC1	3.554
RC2	4.545
RC3	4.059
PE1	1.566
PE2	1.957
PE3	2.812
PE4	2.960
BI1	1.569
BI2	1.741
BI3	1.394
BI4	1.473
PCD1	2.072
PDC2	2.130
PDC3	1.250

Direct effects were examined first. The results of the analysis aimed to explore the direct effects of PE, PDC, SI, PCO and RC on BI are reported in Table 10, showing results for the direct hypothesis from H1 to H5, and H6a, H7a, H8a, and H9a. The first column outlines the tested relationships, while the second column identifies the associated hypotheses. The third column indicates the support status for each hypothesis. The remaining columns report the original sample values, sample means, standard deviations, T-statistics, and p-values, providing the basis for assessing statistical significance, as reported in the following Table.

Results show that PE emerged as the strongest predictor of BI

Table 8
Outer loading.

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
FC1 <- FC	0.714	0.710	0.042	17.011	0.000
PCO1 <- PCO	0.601	0.590	0.086	7.021	0.000
FC2 <- FC	0.732	0.730	0.034	21.747	0.000
PCO2 <- PCO	0.704	0.694	0.070	10.080	0.000
PCO3 <- PCO	0.948	0.945	0.027	34.661	0.000
RC1 <- RC	0.927	0.926	0.009	103.954	0.000
RC2 <- RC	0.955	0.955	0.005	196.725	0.000
RC3 <- RC	0.939	0.939	0.009	102.049	0.000
AIG3 <- AIG	0.744	0.745	0.035	21.142	0.000
PE1 <- PE	0.701	0.701	0.027	25.622	0.000
PE2 <- PE	0.828	0.828	0.016	51.615	0.000
PE3 <- PE	0.855	0.855	0.012	71.793	0.000
PE4 <- PE	0.871	0.871	0.012	75.702	0.000
BI1 <- BI	0.762	0.762	0.021	36.512	0.000
BI2 <- BI	0.797	0.796	0.019	42.914	0.000
BI3 <- BI	0.712	0.711	0.027	26.201	0.000
BI4 <- BI	0.775	0.775	0.020	38.994	0.000
FC4<− FC	0.728	0.725	0.036	19.974	0.000
PDC1 <- EE	0.889	0.887	0.016	55.392	0.000
PDC2 <- EE	0.904	0.903	0.015	59.951	0.000
PDC3 <- EE	0.653	0.650	0.048	13.581	0.000

Table 9
Cross loading.

	BI	PDC	AIG	PE	RC	PCO
AIG1	0.163	0.061	0.714	0.279	0.139	0.185
AIG2	0.239	0.000	0.732	0.304	0.170	0.276
AIG3	0.417	0.123	0.744	0.435	0.219	0.201
AIG4	0.242	0.001	0.728	0.312	0.111	0.299
PCO1	0.102	0.023	0.303	0.131	0.011	0.601
PCO2	0.103	−0.001	0.278	0.151	0.006	0.704
PCO3	0.287	0.096	0.264	0.235	0.200	0.948
RC1	0.244	0.226	0.208	0.245	0.927	0.137
RC2	0.311	0.266	0.247	0.292	0.955	0.174
RC3	0.254	0.276	0.198	0.236	0.939	0.131
PE1	0.447	0.183	0.372	0.701	0.226	0.222
PE2	0.559	0.260	0.351	0.828	0.287	0.195
PE3	0.632	0.160	0.405	0.855	0.208	0.169
PE4	0.604	0.121	0.441	0.871	0.186	0.206
BI1	0.762	0.033	0.390	0.583	0.148	0.152
BI2	0.797	0.103	0.266	0.499	0.210	0.145
BI3	0.712	0.327	0.188	0.477	0.273	0.162
BI4	0.775	0.219	0.359	0.540	0.255	0.333
PDC1	0.198	0.889	0.065	0.201	0.244	0.050
PDC2	0.195	0.904	0.012	0.177	0.272	0.042
PDC3	0.147	0.653	0.161	0.173	0.133	0.135

($\beta = 0.607$, $p < 0.001$), corroborating prior literature, which posits that clinicians are more inclined to adopt AI systems when they believe such tools will enhance their performance and clinical outcomes. RC also showed a robust and statistically significant direct effect on BI ($\beta = 0.287$, $p < 0.001$), validating its conceptual relevance in the surgical context. This finding highlights that ethical clarity and perceived accountability are not peripheral considerations, but central determinants of AI acceptance. The strength of this relationship suggests that when surgeons feel that responsibility is appropriately distributed and transparent, their intention to adopt AI increases considerably.

PCO significantly influenced BI ($\beta = 0.082$, $p = 0.007$), albeit with a smaller effect size. This suggests that peer and institutional endorsement plays a meaningful, though secondary, role in technology acceptance. In contrast, PDC and AIG demonstrated weaker and only marginally significant effects on BI ($\beta = 0.054$, $p = 0.080$ and $\beta = 0.057$, $p = 0.128$, respectively). These results suggest that while usability and infrastructure support are necessary, they are not sufficient drivers of intention among surgical professionals unless accompanied by perceived responsibility and performance outcomes.

RC positively influenced PE ($\beta = 0.276$, $p < 0.001$), PDC ($\beta = 0.273$, $p < 0.001$), PCO ($\beta = 0.158$, $p < 0.001$), and AIG ($\beta = 0.233$, $p < 0.001$). These results reinforce the theoretical proposition that perceptions of responsibility not only shape behavioral intention directly but also condition the extent to which other facilitators are perceived as credible and effective.

The mediating effects of PE, PDC, PCO and AIG on the relationship between RC and BI are reported in Table 11.

Interestingly, the mediation analysis provided additional insights into the mechanism through which responsibility influences intention. Specifically, PE mediated the relationship between RC and BI significantly ($\beta = 0.168$, $p < 0.001$), suggesting that when ethical and professional responsibility is clear, surgeons are more likely to view AI as a performance-enhancing tool, thereby reinforcing their intention to adopt it. SI also mediated the RC–BI path ($\beta = 0.013$, $p = 0.025$), though the effect was modest.

By contrast, PDC and AIG served as weaker mediators. The indirect effects via PDC ($\beta = 0.015$, $p = 0.099$) and FC ($\beta = 0.013$, $p = 0.139$) did not reach conventional levels of significance, indicating that while responsibility improves perceptions of usability and infrastructural support, these pathways contribute less to explaining variance in behavioral intention. This result may reflect the high cognitive and ethical stakes of surgical environments, where affective and normative concerns outweigh concerns about ease-of-use or logistical enablers.

5. Discussion

This study set out to explore how trauma and emergency surgeons perceive the adoption of AI-based decision-support tools in high-stakes clinical environments. Moving beyond a strict hypothesis-by-hypothesis interpretation, the discussion is organized thematically to highlight the study's central insights and their theoretical, managerial, and societal implications.

5.1. Ethical drivers of AI adoption: the central role of shared accountability

The most salient finding of this study concerns the role of shared accountability perceptions in shaping surgeons' intentions to adopt AI tools. Shared accountability emerged not only as a significant direct predictor of behavioral intention but also as a foundational belief that shapes how surgeons evaluate AI's performance potential.

This result substantiates the argument that AI adoption in surgery cannot be fully explained by instrumental considerations alone (Venkatesh, 2022). In high-stakes clinical work, where errors can have irreversible consequences, surgeons' willingness to engage with AI is contingent on whether responsibility for AI-assisted decisions is perceived as appropriately distributed among clinicians, technology providers, and data managers. This extends existing technology adoption research by demonstrating that normative governance beliefs, rather than individual attitudes or perceived risks alone, play a decisive role in adoption decisions (Holzinger et al., 2020; van Wynsberghe,

Table 10
Total effects.

Relationship	Hypothesis	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
PE - > BI	H1	0.607	0.607	0.032	18.981	0.000
PDC - > BI	H2	0.054	0.056	0.031	1.751	0.080
PCO- > BI	H3	0.082	0.083	0.030	2.701	0.007
AIG - > BI	H4	0.057	0.058	0.037	1.521	0.128
RC - > BI	H5	0.287	0.288	0.039	7.345	0.000
RC - > PE	H6a	0.276	0.277	0.040	6.897	0.000
RC - > PDC	H7a	0.273	0.275	0.038	7.124	0.000
RC - > PCO	H8a	0.158	0.161	0.039	4.011	0.000
RC - > AIG	H9a	0.233	0.235	0.037	6.223	0.000

Table 11
Specific indirect effects.

	Hypothesis	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
RC - > PE - > BI	H6b	0.168	0.168	0.026	6.436	0.000
RC - > PDC - > BI	H7b	0.015	0.015	0.009	1.652	0.099
RC - > PCO - > BI	H8b	0.013	0.013	0.006	2.246	0.025
RC - > AIG - > BI	H9b	0.013	0.014	0.009	1.480	0.139

2015).

Importantly, shared accountability perceptions differ conceptually from perceived risk, trust, or liability anxiety. While those constructs focus on outcome uncertainty or emotional responses to potential harm (Gupta et al., 2021; Russell et al., 2015) shared accountability captures surgeons' beliefs about how responsibility should be allocated in socio-technical systems (Floridi et al., 2018). This normative orientation helps explain why surgeons may reject technically sophisticated AI tools if accountability arrangements remain ambiguous, even when performance benefits are evident.

Positioning shared accountability as an antecedent rather than a moderator is consistent with the view that accountability beliefs are pre-evaluative orientations that shape subsequent assessments of AI attributes (Venkatesh, 2022). Surgeons who endorse shared accountability are more likely to perceive AI as a governable extension of clinical practice rather than as an uncontrollable source of medico-legal exposure (Topol, 2019).

5.2. Technical performance as the primary instrumental driver

Consistent with prior technology adoption literature, performance expectancy emerged as the strongest predictor of behavioral intention. This finding reinforces the pragmatic orientation of surgeons, for whom AI adoption is ultimately justified by its capacity to improve diagnostic accuracy, clinical decision-making, and patient outcomes (Dwivedi et al., 2021; Loftus et al., 2021; Venkatesh et al., 2003).

However, the present study adds nuance by showing that performance evaluations are not independent of governance considerations. Shared accountability perceptions significantly influenced performance expectancy, suggesting that surgeons are more likely to recognize AI's clinical value when responsibility for AI-assisted decisions is clearly distributed. This aligns with prior work emphasizing that AI systems designed to preserve human oversight and allow validation or override are perceived as more useful and trustworthy (Jiang et al., 2017; Stanfill and Marc, 2019; Topol, 2019).

By contrast, perceived diagnostic complexity did not directly predict adoption intention. While AI has been widely proposed as a tool to manage diagnostic uncertainty and cognitive load (Loftus et al., 2020; O'sullivan and Schofield, 2018), the non-significant effect suggests that complexity is a structural feature of surgical work that surgeons already accept as inherent. In such contexts, AI is evaluated less as a response to complexity itself and more in terms of its ability to deliver reliable performance improvements within acceptable accountability frameworks.

5.3. Governance climate and social dynamics: necessary but not sufficient

The responsible AI governance climate did not exert a significant direct effect on behavioral intention. This result should not be interpreted as evidence that governance is unimportant. Rather, it suggests that ethical and regulatory expectations function as background enabling conditions rather than primary motivators of adoption.

Prior research emphasizes that data governance, transparency, explainability, and cybersecurity are critical for safe AI deployment in healthcare (Esteva et al., 2019; Garcia-Perez et al., 2023; Rieke et al., 2020). However, in high-stakes clinical environments, surgeons may assume that such safeguards should already be in place as prerequisites for deployment, rather than viewing them as drivers of individual adoption decisions. This interpretation is consistent with findings that performance considerations tend to dominate adoption judgments under time pressure and clinical risk (Loftus et al., 2021; Venkatesh, 2022).

Similarly, patient-centered communication orientation exhibited only a modest relationship with adoption intention. While patient engagement and shared decision-making are well-established professional values in surgery (Cobianchi et al., 2023; Yu et al., 2018), they appear secondary to concerns about performance and accountability when surgeons evaluate AI tools. In emergency and trauma settings, where decisions are often made under severe time constraints, communicative considerations may be subordinated to medico-legal responsibility and outcome reliability (Loftus et al., 2020; De Simone et al., 2021).

5.4. Implications for sustainable healthcare and institutional integrity

The findings have direct implications for sustainable healthcare systems. By reducing accountability ambiguity, shared accountability frameworks may lower barriers to AI adoption, indirectly supporting SDG 3 by enabling safer and more effective clinical decision-making (Dal Mas et al., 2023; Sulaieva et al., 2024).

More importantly, this study offers a concrete contribution to SDG 16 by identifying accountability clarity as a micro-foundation of institutional integrity in AI-enabled healthcare. Clear accountability regimes enable auditability of AI-assisted decisions, support due process by clarifying how decisions are made and contested, and foster institutional trust among clinicians, patients, and regulators (Floridi et al., 2018; van Wynsberghe, 2021).

In this sense, shared accountability perceptions translate abstract governance principles into operational conditions shaping AI adoption at the clinical level, reinforcing the role of strong institutions in managing emerging technologies within healthcare systems.

5.5. Managerial implications

Beyond its theoretical contributions, this study yields practical implications for healthcare leaders, policymakers, and technology developers. First, AI implementation strategies should be designed with explicit ethical governance mechanisms that delineate responsibilities across clinical, technical, and institutional domains. Second, investments in training and infrastructure must be accompanied by communication strategies that reinforce shared responsibility, thereby fostering trust and reducing ambiguity.

For developers, this means designing systems that allow for human oversight, transparency in decision-making logic, and user input. For institutions, it entails establishing policies for explainability, data protection, and liability management that are aligned with the expectations and ethical frameworks of clinical practice. Finally, for policymakers and regulators, our findings suggest the importance of legislative clarity on AI accountability, particularly in fields like surgery, where autonomy and risk converge.

6. Conclusions

AI has the potential to revolutionize decision-making in the healthcare system, especially in trauma and emergency surgery, by offering significant benefits such as improved diagnostics, enhanced clinical outcomes, and greater operational efficiency (Loftus et al., 2020; Rajpurkar et al., 2022; Secinaro et al., 2021). This study contributes to the growing literature on AI adoption in healthcare by offering an empirically grounded, context-sensitive analysis of surgeons' adoption intentions in trauma and emergency settings. Rather than testing the UTAUT model per se, the study advances an exploratory framework informed by UTAUT principles but adapted to the ethical and organizational realities of high-stakes clinical work.

The findings demonstrate that shared accountability perceptions and performance expectancy are the primary drivers of AI adoption intentions among surgeons. Accountability emerges not merely as a legal or ethical afterthought but as a central governance condition that shapes how technological benefits are perceived and evaluated. By contrast, diagnostic complexity and governance climate, while important contextual factors, do not directly motivate adoption decisions.

From a theoretical perspective, this study extends technology adoption research by foregrounding normative governance beliefs as antecedents of technology evaluation in socio-technical systems characterized by distributed agency. It underscores the need to move beyond individual-level acceptance models when studying AI adoption in professional domains where responsibility cannot be singularly assigned.

From a managerial and policy perspective, the results suggest that accelerating responsible AI adoption in surgery requires more than technical validation. Clinical leaders and policymakers should prioritize the design of explicit accountability protocols that delineate the roles of surgeons, institutions, technology developers, and data managers. Aligning such protocols with regulatory frameworks, such as GDPR transparency obligations, emerging AI governance regimes, and medical device regulations, can enhance institutional trust and adoption readiness.

This study has limitations. The cross-sectional design restricts causal inference, the sample is geographically skewed toward European and American contexts, and the accountability construct captures normative preferences rather than perceived accountability clarity or liability anxiety. Future research should develop richer, multidimensional accountability measures and examine how legal and cultural contexts moderate AI adoption dynamics.

In conclusion, AI adoption in surgery is not solely a question of technological capability. It is fundamentally a question of governance. Clarifying who is accountable when humans and algorithms jointly shape clinical decisions may be the decisive factor in realizing AI's potential for sustainable, trustworthy healthcare systems.

CRediT authorship contribution statement

Francesca Dal Mas: Conceptualization, Data curation, Funding acquisition, Investigation, Methodology, Project administration, Resources, Validation, Writing – original draft. **Maurizio Massaro:** Data curation, Formal analysis, Methodology, Visualization, Writing – original draft. **Justyna Fijałkowska:** Writing – review & editing. **Valentina Ndou:** Conceptualization, Writing – review & editing. **Elisabetta Raguseo:** Conceptualization, Formal analysis, Methodology, Supervision, Writing – review & editing.

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Data availability

The authors do not have permission to share data.

References

Ajzen, I., 1991. The theory of planned behavior. Organ. Behav. Hum. Decis. Process. 50 (2), 179–211. https://doi.org/10.1016/0749-5978(91)90020-T.

Ajzen, I., Fishbein, M., 1977. Attitude-behavior relations: A theoretical analysis and review of empirical research. Psychol. Bullet. 84 (5), 888–918. https://doi.org/10.1037/0033-2909.84.5.888, 9, 1977.

Akwang, N.E., 2021. A study of librarians' perceptions and adoption of web 2.0 technologies in academic libraries in Akwa Ibom state, Nigeria. J. Acad. Librarian 47 (2), 102299. https://doi.org/10.1016/j.acalib.2020.102299.

Appio, F.P., La Torre, D., Lazzeri, F., Masri, H., Schiavone, F., 2023. Impact of Artificial Intelligence in Business and Society. Opportunities and Challenges. Routledge. https://doi.org/10.4324/9781003304616.

Baabdullah, A.M., Alalwan, A.A., Algharabat, R.S., Metri, B., Rana, N.P., 2022. Virtual agents and flow experience: an empirical examination of AI-powered chatbots. Technol. Forecast. Soc. Change 181, 121772. https://doi.org/10.1016/j.techfore.2022.121772.

Balch, J., Upchurch, G.R., Bihorac, A., Loftus, T.J., 2021. Bridging the artificial intelligence valley of death in surgical decision-making. Surgery 169 (4), 746–748. https://doi.org/10.1016/j.surg.2021.01.008.

Bashshur, R., Shannon, G., Krupinski, E., Grigsby, J., 2011. The taxonomy of telemedicine. Telemed. J. e Health: The Official J. American Telemedicine Association 17 (6), 484–494. https://doi.org/10.1089/tmj.2011.0103. United States.

Basile, L.J., Carbonara, N., Pellegrino, R., Panniello, U., 2023. Business intelligence in the healthcare industry: the utilization of a data-driven approach to support clinical decision making. Technovation 120. https://doi.org/10.1016/j.technovation.2022.102482.

Bertsimas, D., Dunn, J., Velmahos, G.C., Kaafarani, H.M.A., 2018. Surgical risk is not linear: derivation and validation of a novel, user-friendly, and machine-learning-based predictive OpTimal trees in emergency surgery risk (POTTER) calculator. Ann. Surg. 268 (4).

Biancone, P., Secinaro, S., Marseglia, R., Calandra, D., 2021. E-health for the future. Managerial perspectives using a multiple case study approach. Technovation, 102406. https://doi.org/10.1016/j.technovation.2021.102406.

Boniol, M., Kunjumen, T., Nair, T.S., Siyam, A., Campbell, J., Diallo, K., 2022. The global health workforce stock and distribution in 2020 and 2030: a threat to equity and 'universal' health coverage? BMJ Glob. Health 7 (6), e009316. https://doi.org/10.1136/bmjgh-2022-009316.

Byerly, S., Maurer, L.R., Mantero, A., Naar, L., An, G., Kaafarani, H.M.A., 2021. Machine learning and artificial intelligence for surgical decision making. Surgical Infections, Mary Ann Liebert, Inc., publishers 22 (6), 626–634. https://doi.org/10.1089/sur.2021.007.

Calinon, S., Bruno, D., Malekzadeh, M.S., Nanayakkara, T., Caldwell, D.G., 2014. Human-robot skills transfer interfaces for a flexible surgical robot. Comput. Methods Progr. Biomed. 116 (2), 81–96. https://doi.org/10.1016/j.cmpb.2013.12.015.

Caputo, F., Cillo, V., Candelo, E., Liu, Y., 2019. Innovating through digital revolution: the role of soft skills and big data in increasing firm performance. Manag. Decis. 57 (8), 2032–2051. https://doi.org/10.1108/MD-07-2018-0833.

Chen, B., Baur, A., Stepniak, M., Wang, J., 2019. Finding the Future of Care Provision: the Role of Smart Hospitals.

Chong, A.Y.-L., Binshan, L., Keng-Boon, O., Raman, M., 2009. Factors affecting the Adoption level of C-Commerce: an empirical Study. J. Comput. Inf. Syst. 50 (2), 13–22. https://doi.org/10.1080/08874417.2009.11645380. Taylor & Francis.

Chua, P.Y., Rezaei, S., Gu, M.-L., Oh, Y., Jambulingam, M., 2018. Elucidating social networking apps decisions. In: Nankai Business Review International, vol. 9. Emerald Publishing Limited, pp. 118–142. https://doi.org/10.1108/NBRI-01-2017-0003, 2.

Cobianchi, L., Dal Mas, F., Agnoletti, V., Ansaloni, A., Biffl, V., Butturini, G., Campostrini, S., et al., 2023a. Time for a paradigm shift in shared decision-making in trauma and emergency surgery? Results from an international survey. World J. Emerg. Surg.

Cobianchi, L., Dal Mas, F., Ansaloni, L., 2022a. Editorial: new frontiers for artificial intelligence in surgical decision making and its organizational impacts. Front. Surg. 9, 933673. https://doi.org/10.3389/fsurg.2022.933673.

Cobianchi, L., Dal Mas, F., Catena, F., Ansaloni, A., 2023b. Artificial Intelligence and clinical Decision-Making in emergency surgery. A research protocol. In: Sousa, M.J., Kumar, P.S., Dal Mas, F., Sousa, S. (Eds.), Advancements in Artificial Intelligence in the Service Sector. Routledge, London.

Cobianchi, L., Dal Mas, F., Massaro, M., Bednarova, R., Biancuzzi, H., Filisetti, C., Barcellini, A., et al., 2022b. Hand in hand: a multistakeholder approach for Co-production of surgical care. Am. J. Surg. 223 (1), 214–215. https://doi.org/10.1016/j.amjsurg.2021.07.053.

Cobianchi, L., Dal Mas, F., Massaro, M., Biffl, W., Catena, F., Coccolini, F., Dionigi, B., et al., 2022c. Diversity and ethics in trauma and acute care surgery teams: results from an international survey. World J. Emerg. Surg. 17 (1), 44. https://doi.org/10.1186/s13017-022-00446-8.

Cobianchi, L., Dal Mas, F., Massaro, M., Fugazzola, P., Coccolini, F., Kluger, Y., Leppäniemi, A., et al., 2021. Team dynamics in emergency surgery teams: results from a first international survey. World J. Emerg. Surg. 16, 47. https://doi.org/10.1186/s13017-021-00389-6.

Cobianchi, L., Piccolo, D., Dal Mas, F., Agnoletti, V., Ansaloni, L., Balch, J., Biffl, W., et al., 2023c. Surgeons ' perspectives on artificial intelligence to support clinical decision - making in trauma and emergency contexts : results from an international survey. World J. Emerg. Surg. 18, 1–17. https://doi.org/10.1186/s13017-022-00467-3.

Cobianchi, L., Verde, J.M., Loftus, T.J., Piccolo, D., Dal Mas, F., Mascagni, P., Garcia Vazquez, A., et al., 2022d. Artificial intelligence and surgery: ethical dilemmas and open issues. J. Am. Coll. Surg. 235 (2), 268–275.

Dal Mas, F., 2024. SDG reporting in healthcare. In: Venturelli, A., Mio, C. (Eds.), The Routledge Handbook of Accounting for the Sustainable Development Goals. Routledge, London.

Dal Mas, F., Garcia-Perez, A., Sousa, M.J., Lopes da Costa, R., Cobianchi, L., 2020. Knowledge translation in the healthcare sector. A structured literature review. Electron. J. Knowl. Manag. 18 (3), 198–211. https://doi.org/10.34190/EJKM.18.03.001.

Dal Mas, F., Massaro, M., Rippa, P., Secundo, G., 2023. The challenges of digital transformation in healthcare: an interdisciplinary literature review, framework, and future research agenda. Technovation 123, 102716. https://doi.org/10.1016/j.technovation.2023.102716.

Davis, F., Davis, F., 1989. Perceived usefulness, perceived ease of use, and user acceptance of information technology. MIS Q. 13, 319. https://doi.org/10.2307/249008.

De Simone, B., Abu-Zidan, F.M., Gumbs, A.A., Chouillard, E., Di Saverio, S., Sartelli, M., Coccolini, F., et al., 2022. Knowledge, attitude, and practice of artificial intelligence in emergency and trauma surgery, the ARIES project: an international web-based survey. World Journal of Emergency Surgery, BioMed Central 17 (1), 10. https://doi.org/10.1186/s13017-022-00413-3.

De Simone, B., Chouillard, E., Sartelli, M., Biffl, W.L., Di Saverio, S., Moore, E.E., Kluger, Y., et al., 2021. The management of surgical patients in the emergency setting during COVID-19 pandemic: the WSES position paper. World J. Emerg. Surg. 16 (1), 14. https://doi.org/10.1186/s13017-021-00349-0.

Dicuonzo, G., Donofrio, F., Fusco, A., Shini, M., 2022. Healthcare system: moving forward with artificial intelligence. Technovation, 102510. https://doi.org/10.1016/j.technovation.2022.102510.

Dwivedi, Y.K., Hughes, L., Ismagilova, E., Aarts, G., Coombs, C., Crick, T., Duan, Y., et al., 2019. Artificial intelligence (AI): multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy. Int. J. Inf. Manag., 101994 https://doi.org/10.1016/j.ijinfomgt.2019.08.002.

Dwivedi, Y.K., Hughes, L., Ismagilova, E., Aarts, G., Coombs, C., Crick, T., Duan, Y., et al., 2021. Artificial Intelligence (AI): multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy. Int. J. Inf. Manag. 57, 101994. https://doi.org/10.1016/j.ijinfomgt.2019.08.002.

Elbanna, S., 2013. Processes and impacts of strategic management: evidence from the public sector in the United Arab Emirates. Int. J. Publ. Adm. 36 (6), 426–439. https://doi.org/10.1080/01900692.2013.772629. Routledge.

Esteva, A., Robicquet, A., Ramsundar, B., Kuleshov, V., DePristo, M., Chou, K., Cui, C., et al., 2019. A guide to deep learning in healthcare. Nat. Med. 25 (1), 24–29. https://doi.org/10.1038/s41591-018-0316-z.

Eysenbach, G., 2004. Improving the quality of web surveys: the Checklist for reporting results of internet E-Surveys (CHERRIES). J. Med. Internet Res. 6 (3), 1–6. https://doi.org/10.2196/jmir.6.3.e34.

Figueroa-Armijos, M., Clark, B.B., da Motta Veiga, S.P., 2022. Ethical perceptions of AI in hiring and organizational trust: the role of performance expectancy and social influence. J. Bus. Ethics. https://doi.org/10.1007/s10551-022-05166-2.

Floridi, L., Cowls, J., Beltrametti, M., Chatila, R., Chazerand, P., Dignum, V., Luetge, C., et al., 2018. AI4People—An ethical framework for a good AI Society: opportunities, risks, principles, and recommendations. Minds Mach. 28 (4), 689–707. https://doi.org/10.1007/s11023-018-9482-5.

Garcia-Perez, A., Cegarra-Navarro, J.G., Sallos, M.P., Martinez-Caro, E., Chinnaswamy, A., 2023. Resilience in healthcare systems: cyber security and digital transformation. Technovation 121, 102583. https://doi.org/10.1016/j.technovation.2022.102583.

Gundersen, T., Bærøe, K., 2022. The future ethics of artificial intelligence in medicine: making sense of collaborative models. Sci. Eng. Ethics 28 (2). https://doi.org/10.1007/s11948-022-00369-2.

Gupta, S., Langhans, S.D., Domisch, S., Fuso-Nerini, F., Felländer, A., Battaglini, M., Tegmark, M., et al., 2021. Assessing whether artificial intelligence is an enabler or an inhibitor of sustainability at indicator level. Transport Eng. 4, 100064. https://doi.org/10.1016/j.treng.2021.100064.

Gursoy, D., Chi, O.H., Lu, L., Nunkoo, R., 2019. Consumers acceptance of artificially intelligent (AI) device use in service delivery. Int. J. Inf. Manag. 49, 157–169. https://doi.org/10.1016/j.ijinfomgt.2019.03.008.

Hair, J.F., Ringle, C.M., Sarstedt, M., 2011. PLS-SEM: indeed a silver bullet. J. Market. Theor. Pract. 19 (2), 139–152. Taylor & Francis.

Hazen B, T., Kung, L., Cegielski, C.G., Allison Jones-Farmer, L., 2014. Performance expectancy and use of enterprise architecture: training as an intervention. J. Enterprise Inf. Manag. 27 (2), 180–196. https://doi.org/10.1108/JEIM-08-2012-0042. Emerald Group Publishing Limited.

Holzinger, A., Carrington, A., Müller, H., 2020. Measuring the quality of explanations: the System Causability Scale (SCS). KI - Künstliche Intelligenz 34 (2), 193–198. https://doi.org/10.1007/s13218-020-00636-z.

Jiang, F., Jiang, Y., Zhi, H., Dong, Y., Li, H., Ma, S., Wang, Y., et al., 2017. Artificial intelligence in healthcare: past, present and future. Stroke and Vascular Neurology, England 2 (4), 230–243. https://doi.org/10.1136/svn-2017-000101.

Johnson-Mann, C.N., Loftus, T.J., Bihorac, A., 2021. Equity and artificial intelligence in surgical care. JAMA Surg. 156 (6), 509. https://doi.org/10.1001/jamasurg.2020.7208.

Khakurel, J., Penzenstadler, B., Porras, J., Knutas, A., Zhang, W., 2018. The rise of artificial intelligence under the lens of sustainability. Technologies. https://doi.org/10.3390/technologies6040100.

Loftus, T.J., Altieri, M.S., Balch, J.A., Abbott, K.L., Choi, J., Marwaha, J.S., Hashimoto, D. A., et al., 2023. Artificial intelligence–enabled decision support in surgery: State-of-the-art and future directions. Ann. Surg. 278 (1).

Loftus, T.J., Filiberto, A.C., Balch, J., Ayzengart, A.L., Tighe, P.J., Rashidi, P., Bihorac, A., et al., 2020a. Intelligent, autonomous machines in surgery. J. Surg. Res. 253, 92–99. https://doi.org/10.1016/j.jss.2020.03.046. Elsevier Inc.

Loftus, T.J., Tighe, P.J., Filiberto, A.C., Balch, J., Upchurch Jr, G.R., Rashidi, P., Bihorac, A., 2020b. Opportunities for machine learning to improve surgical ward safety. Am. J. Surg. 220 (4), 905–913. Elsevier.

Loftus, T.J., Tighe, P.J., Filiberto, A.C., Efron, P.A., Brakenridge, S.C., Mohr, A.M., Rashidi, P., et al., 2020c. Artificial intelligence and surgical decision-making. JAMA Surg. 155 (2), 148–158. https://doi.org/10.1001/jamasurg.2019.4917.

Loftus, T.J., Upchurch, G.R., Bihorac, A., 2021. Building an artificial intelligence–competent surgical workforce. JAMA Surg. 156 (6), 511. https://doi.org/10.1001/jamasurg.2021.0045.

Loftus, T.J., Vlaar, A.P.J., Hung, A.J., Bihorac, A., Dennis, B.M., Juillard, C., Hashimoto, D.A., et al., 2022. Executive summary of the artificial intelligence in surgery series. Surgery 171 (5), 1435–1439. https://doi.org/10.1016/j.surg.2021.10.047. Elsevier Inc.

MacKenzie, S.B., Podsakoff, P.M., Podsakoff, N.P., 2011. Construct measurement and validation procedures in MIS and behavioral research: integrating new and existing techniques. Management Information Systems Quarterly 35 (2). https://doi.org/10.2307/23044045, 293-A5.

Madani, A., Namazi, B., Altieri, M.S., Hashimoto, D.A., Rivera, A.M., Pucher, P.H., Navarrete-Welton, A., et al., 2020. Artificial intelligence for intraoperative guidance: using semantic segmentation to identify surgical anatomy during laparoscopic cholecystectomy. Ann. Surg. https://doi.org/10.1097/SLA.0000000000004594.

Makridakis, S., 2017. The forthcoming Artificial Intelligence (AI) revolution: its impact on society and firms. Futures 90, 46–60. https://doi.org/10.1016/j.futures.2017.03.006.

Mancuso, I., Petruzzelli, A.M., Panniello, U., Vaia, G., 2025. The bright and dark sides of AI innovation for sustainable development: understanding the paradoxical tension between value creation and value destruction. Technovation 143, 103232. https://doi.org/10.1016/j.technovation.2025.103232.

Mascagni, P., Alapatt, D., Urade, T., Vardazaryan, A., Mutter, D., Marescaux, J., Costamagna, G., et al., 2021. A computer vision platform to automatically locate critical events in surgical videos: documenting safety in laparoscopic cholecystectomy. Annals of Surgery, United States 274 (1), e93–e95. https://doi.org/10.1097/SLA.0000000000004736.

Melián-González, S., Desiderio, G.-T., Bulchand-Gidumal, J., 2021. Predicting the intentions to use chatbots for travel and tourism. Curr. Issues Tourism 24 (2), 192–210. https://doi.org/10.1080/13683500.2019.1706457. Routledge.

Merli, R., Preziosi, M., Acampora, A., Ali, F., 2019. Why should hotels go green? Insights from guests experience in green hotels. Int. J. Hospit. Manag. 81, 169–179. Elsevier.

Müller, R., Jugdev, K., 2012. Critical success factors in projects. In: Söderland, J., Geraldi, J. (Eds.), International Journal of Managing Projects in Business, vol. 5. Emerald Group Publishing Limited, pp. 757–775. https://doi.org/10.1108/17538371211269040, 4.

Muehlematter, U.J., Daniore, P., Vokinger, K.N., 2021. Approval of artificial intelligence and machine learning-based medical devices in the USA and Europe (2015–20): a comparative analysis. Lancet Digit. Health 3 (3), e195–e203. https://doi.org/

10.1016/S2589-7500(20)30292-2. The Author(s). Published by Elsevier Ltd. This is an Open Access article under the CC BY-NC-ND 4.0 license.
Nishant, R., Kennedy, M., Corbett, J., 2020. Artificial intelligence for sustainability: challenges, opportunities, and a research agenda. Int. J. Inf. Manag. 53, 102104. https://doi.org/10.1016/j.ijinfomgt.2020.102104.
Nooteboom, B., 1994. Innovation and diffusion in small firms: theory and evidence. Small Bus. Econ. 6 (5), 327–347. https://doi.org/10.1007/BF01065137.
Norzelan, N.A., Mohamed, I.S., Mohamad, M., 2024. Technology acceptance of artificial intelligence (AI) among heads of finance and accounting units in the shared service industry. Technol. Forecast. Soc. Change 198, 123022. https://doi.org/10.1016/j.techfore.2023.123022.
Oliveira, T., Thomas, M., Espadanal, M., 2014. Assessing the determinants of cloud computing adoption: an analysis of the manufacturing and services sectors. Inf. Manag. 51 (5), 497–510. https://doi.org/10.1016/j.im.2014.03.006.
Oppioli, M., Sousa, M.J., Sousa, M., de Nuccio, E., 2023. The role of artificial intelligence for management decision: a structured literature review. Management Decision. Emerald Publishing Limited. https://doi.org/10.1108/MD-08-2023-1331. Vol. ahead-of-p No. ahead-of-print.
O'sullivan, E.D., Schofield, S.J., 2018. Cognitive bias clinical medicine. J. Roy. Coll. Phys. Edinb. 48 (3), 225–232. https://doi.org/10.4997/JRCPE.2018.306.
Panesar, S., Cagle, Y., Chander, D., Morey, J., Fernandez-Miranda, J., Kliot, M., 2019. Artificial intelligence and the future of surgical robotics. Ann. Surg. 270 (2).
Pillai, R., Ghanghorkar, Y., Sivathanu, B., Algharabat, R., Rana, N.P., 2024. Adoption of artificial intelligence (AI) based employee experience (EEX) chatbots. Inf. Technol. People 37 (1), 449–478. https://doi.org/10.1108/ITP-04-2022-0287. Emerald Publishing Limited.
Pradarelli, J.C., Gupta, A., Lipsitz, S., Blair, P.G., Sachdeva, A.K., Smink, D.S., Yule, S., 2020. Assessment of the Non-Technical Skills for surgeons (NOTSS) framework in the USA. Br. J. Surg. 107 (9), 1137–1144. https://doi.org/10.1002/bjs.11607. England.
Rajpurkar, P., Chen, E., Banerjee, O., Topol, E.J., 2022. AI in health and medicine. Nat. Med. 28 (1), 31–38. https://doi.org/10.1038/s41591-021-01614-0. Springer US.
Rieke, N., Hancox, J., Li, W., Milletarì, F., Roth, H.R., Albarqouni, S., Bakas, S., et al., 2020. The future of digital health with federated learning. npj Digit. Med. 3 (1), 119. https://doi.org/10.1038/s41746-020-00323-1.
Russell, S., Hauert, S., Altman, R., Veloso, M., 2015. Robotics: ethics of artificial intelligence. Nature 521 (7553), 415–418.
Saeed, W., Omlin, C., 2023. Explainable AI (XAI): a systematic meta-survey of current challenges and future opportunities. Knowl. Base Syst. 263. https://doi.org/10.1016/j.knosys.2023.110273.
Secinaro, S., Calandra, D., Secinaro, A., Muthurangu, V., Biancone, P., 2021. The role of artificial intelligence in healthcare: a structured literature review. BMC Medical Informatics and Decision Making, BioMed Central 21 (1), 1–23. https://doi.org/10.1186/s12911-021-01488-9.
Shanafelt, T.D., Balch, C.M., Bechamps, G., Russell, T., Dyrbye, L., Satele, D., Collicott, P., et al., 2010. Burnout and medical errors among American surgeons. Ann. Surg. 251 (6).
Stanfill, M.H., Marc, D.T., 2019. Health information management: implications of artificial intelligence on healthcare data and information management. Yearbook of Medical Informatics 28 (1), 56–64. https://doi.org/10.1055/s-0039-1677913.
Sulaieva, O., Dudin, O., Koshyk, O., Panko, M., Kobyliak, N., 2024. Digital pathology implementation in cancer diagnostics: towards informed decision-making. Front. Digit. Health 6, 1358305. https://doi.org/10.3389/fdgth.2024.1358305. Switzerland.
Teo, T., 2006. Attitudes toward computers: a study of post-secondary students in Singapore. Interact. Learn. Environ. 14 (1), 17–24. https://doi.org/10.1080/10494820600616406. Routledge.
Topol, E.J., 2019. High-performance medicine: the convergence of human and artificial intelligence. Nature Medicine, United States 25 (1), 44–56. https://doi.org/10.1038/s41591-018-0300-7.
United Nations, 2015. The 17 goals. Department of Economic. Social Affairs, Sustainable Develop. available at: https://sdgs.un.org/goals. (Accessed 15 January 2022).
van Wynsberghe, A., 2015. Healthcare Robots: Ethics, Design and Implementation. Routledge, London. https://doi.org/10.4324/9781315586397.
van Wynsberghe, A., 2021. Sustainable AI: AI for sustainability and the sustainability of AI. AI and Ethics 1 (3), 213–218. https://doi.org/10.1007/s43681-021-00043-6.
Venkatesh, V., 2022. Adoption and use of AI tools: a research agenda grounded in UTAUT. Ann. Oper. Res. 308 (1), 641–652. https://doi.org/10.1007/s10479-020-03918-9.
Venkatesh, V., Morris, M., Davis, G.B., Davis, F.D., 2003. User acceptance of information technology: toward a unified view. MIS Q. 27 (3), 425–478.
Venkatesh, V., Thong, J.Y.L., Xu, X., 2012. Consumer acceptance and use of information technology: extending the unified theory of acceptance and use of technology. MIS Quarterly, Management Information Systems Res. Center 36 (1), 157–178. https://doi.org/10.2307/41410412. University of Minnesota.
Venkatesh, V., Thong, J.Y.L., Xu, X., 2016. Unified theory of acceptance and use of technology: a synthesis and the road ahead. J. Assoc. Inf. Syst. Online 17 (5), 328–376. https://doi.org/10.17705/1jais.00428.
Venkatesh, V., Davis, F., 2000. A theoretical extension of the technology acceptance model: four longitudinal field studies. Manag. Sci. 46, 186–204. https://doi.org/10.1287/mnsc.46.2.186.11926.
Vinuesa, R., Azizpour, H., Leite, I., Balaam, M., Dignum, V., Domisch, S., Felländer, A., et al., 2020. The role of artificial intelligence in achieving the sustainable development goals. Nat. Commun. 11 (1), 233. https://doi.org/10.1038/s41467-019-14108-y.
Weprin, S.A., Meyer, D., Li, R., Carbonara, U., Crocerossa, F., Kim, F.J., Autorino, R., et al., 2021. Incidence and OR team awareness of 'near-miss' and retained surgical sharps: a national survey on United States operating rooms. Patient Saf. Surg. 15 (1), 14. https://doi.org/10.1186/s13037-021-00287-5.
Williams, M.D., Rana, N.P., Dwivedi, Y.K., 2015. The unified theory of acceptance and use of technology (UTAUT): a literature review. J. Enterprise Inf. Manag. 28 (3), 443–488. https://doi.org/10.1108/JEIM-09-2014-0088. Emerald Group Publishing Limited.
World Society of Emergency Surgery, 2022. Wses guidelines. WSES Guidelines available at: https://www.wses.org.uk/guidelines. (Accessed 4 October 2022).
Yu, K.-H., Beam, A.L., Kohane, I.S., 2018. Artificial intelligence in healthcare. Nat. Biomed. Eng. 2 (10), 719–731. https://doi.org/10.1038/s41551-018-0305-z.