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Medical practitioner's adoption of intelligent clinical diagnostic decision support systems: A mixed-methods study

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A R T I C L E I N F O

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A B S T R A C T

Artificial intelligence-based clinical diagnostic decision support systems promise transformational improvements in doctors' efficiency and accuracy. Nevertheless, low adoption rates suggest that this innovation could fail without adequate uptake. This study uses a mixed-methods approach to develop and test a model based on theories of Unified Theory of Acceptance and Use of Technology, status quo bias, and technology trust. The results show that performance expectancy, effort expectancy, social influence, initial trust, and resistance to change predict intention to use. Further, inertia, perceived threat, and risks (medico-legal and performance) determine resistance to change. Measures for alleviating resistance and improving adoption are proposed.

1. Introduction

Artificial intelligence (AI) is an umbrella term that represents sciences and technologies that use machines to mimic, extend, or improve human intelligence [1]. It denotes "the ability of a machine to learn from experience, adjust to new inputs, and perform human-like tasks" [2]. AI has been in existence for over six decades and has been through several ups ("AI Springs") and downs ("AI Winters"). The recent revitalization of AI is primarily attributable to the progress made in big data technologies and advanced machine learning (ML) techniques (e.g., deep learning) [2]. It is being adopted across the industries for its ability to improve performance/precision, efficiency, and to reduce cost. In healthcare, AI promises improved care and patient outcomes through early detection, improvement in workflow, reduction in error and cost [3]. The commercial use of AI in healthcare has been growing exponentially since 2016, and the size of the market is projected to reach $36.1 Bn by 2025 [4].

An Institute of Medicine report [5] on the magnitude and consequence of preventable medical errors (44,000–98,000 deaths per year in the USA) brought the issue of "human errors" to the forefront of public health debates across the world. Human error is now recognized as a key contributor to adverse events in healthcare [5]. Specifically, in medical diagnosis, human errors often lead to misses, delays, and adverse health consequences [5,6]. According to estimates, 12 mn adults in the USA alone suffer a diagnostic error every year [6]. In medical imaging, the average diagnostic error rate is around 30% [7]. It ranges from 3 to 5% in routine cases [8], from 31 to 37% in oncologic computed tomography (CT) [9], and up to 61% in mammography screening [10]. Case volume, human fatigue, incorrect patient positioning, and anatomical variation can all contribute to diagnostic errors [7,8].

It is in this setting that emerging AI-based medical diagnostics becomes particularly useful. There is an increasing amount of clinical evidence to believe that AI models can help detect anomalies in the medical image in a fraction of a time taken by the human expert with comparable or even superior accuracy levels [11,12]. The promise of AI lies in its ability to identify patterns that can elude human experts, either because the signs are too subtle or involve highly complex decision scenarios [13]. This is especially valuable in developing countries, such as India, where the medical needs of the rising population are met with inadequate resources for intensive diagnostics in remote areas. With a population of over 135 billion, India has less than 10,000 radiologists [14]. The highly skewed radiologist to patient ratio indicates that early and timely detection is a significant challenge.

AI is not new to medical diagnosis; it was used in clinical decision support systems (CDSS) since the 1970s. Such systems, however, typically used algorithms with a large set of pre-programmed rules [15] in contrast to the advanced ML algorithms that are being used today, which can automatically learn from clinical data. An "intelligent" clinical diagnostic decision support system (ICDDSS) can be defined as "an AI-based decision support system that assists a clinician with one or more component steps of the diagnostic process" [16]. Despite the advancements made in ICDDSS technology and the observable benefits,

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the adoption has been slower than anticipated [17-21].

Our review of related literature reveals that despite the boom in the ICDDSS market, there is a paucity of research on this topic [19]. The available research is sparse and fragmented, and does not provide a comprehensive understanding of the determinants of adoption from the perspective of the primary stakeholders, "the medical practitioners" [19]. Further, prior research on similar technologies may not sufficiently explain the adoption of the novel AI-based ICDDSS due to its unique characteristics (autonomous decision-making, self-learning ability, accuracy levels surpassing experts, and non-transparent nature of the algorithms); which give rise to a plethora of new concerns, such as the threat to professional autonomy, fear of replacement, dependency, concerns about patient safety, and legal liability of misdiagnosis [18, 22-24].

Prior research in the healthcare information systems (IS) suggests that a specific reason for the slow adoption of healthcare IS is user resistance to "IS induced change" [25-29]. A recent case study on the failure of an AI system implementation in a hospital setting found that the root causes of the failure lie in users' resistance behaviors to the AI system [30]. The physicians perceived the AI system as an invasive entity rather than as a useful tool due to the highly autonomous and non-transparent nature of the system [30]. These unique characteristics of the system triggered a fear of loss of autonomy in decision-making among the physicians. Similarly, the case of the failure of IBM Watson (ICDDSS for cancer diagnosis) to achieve widespread clinical adoption also echoes the need to anticipate and address user resistance to prevent non-adoption of healthcare AI systems [31].

From the literature, it is evident that the integration of AI systems into existing routines and processes of healthcare work often involves disruptive changes and can lead to resistance [24,30,31]. Bhattacharjee and Hikmet [28] conceptualized this user resistance to IT as a "generalized opposition to change engendered by the expected adverse consequences of change." According to them, "user resistance to IT is not focused so much on a specific IT, but on the change from the status quo caused by IT usage" [28]. They argued that resistance to (IT-induced) change is not a mirror opposite to IT adoption, but an antecedent to it. Moreover, due to the higher tendency for maintaining the status quo than other professional groups, medical practitioners are prone to resist change [26,28]. Although the literature is vocal about the presence of users' resistance to change [23,32] and its role as a barrier to AI adoption [30,33,34], empirical research into its antecedents and consequences is scant [32]. This void in the literature requires further investigation. Moreover, prior studies have exclusively focused on positive (enabling) perceptions of adoption without considering the influence of negative factors (inhibitors), which may impede the adoption [22,35,36]. From a practical standpoint, understanding why medical practitioners would resist ICDDSS will help the stakeholders to devise strategies to minimize resistance [25]. Thus, a comprehensive assessment of the factors (both enabling and inhibiting) influencing the medical practitioners' intentions to use ICDDSS is deemed essential. Hence, this study seeks to answer the following research questions:

> **RQ1.** *What are the factors (enabling and inhibiting) that determine medical practitioners' intentions to use ICDDSS?*
> **RQ2.** *What factors determine the medical practitioners' resistance to (the change induced by the introduction of) ICDDSS in clinical practice?*
> **RQ3.** *How does the medical practitioners' resistance to (the change induced by the introduction of) ICDDSS influence his/her intentions to use ICDDSS?*

We adopted a mixed-methods empirical design [37] consisting of an exploratory qualitative study followed by a confirmatory quantitative survey to address the research questions. Our study makes the following contributions to theory and practice. First, the study extends the IS adoption literature by introducing a new adoption object, ICDDSS. Second, it integrates the technology use and user resistance theories to examine the overall change related to the introduction of ICDDSS in medical practice. Third, it contributes to the user resistance literature by identifying the determinants of resistance to change in the context. Fourth, it validates the mediating role of initial trust in technology and resistance to change in the ICDDSS adoption decision-making. In addition, the study operationalizes the novel construct "medico-legal risk" and tests its role in the adoption. This work could guide practitioners in formulating appropriate intervention strategies to minimize user resistance during the implementation of ICDDSS. It could also aid designers in designing ICDDSS that are purposeful and acceptable to their end-users. The study also persuades policymakers to craft new legal standards for minimizing the users' medico-legal risk associated with ICDDSS usage. The remaining part of the paper is structured as follows: in the following section, we summarize the background of the study and related literature. It is followed by the development of hypotheses. Subsequently, the methodology, analysis, and results are presented. The paper concludes with a discussion of the findings, theoretical/practical implications, and future research directions.

2. Literature review

2.1. Background

2.1.1. Artificial intelligence in healthcare

AI is entering the mainstream of clinical medicine [38,39]. The use of ML in medical imaging is not new; good old-fashioned AI has been used since the early 1970s, e.g., simple neural networks have been used to interpret electrocardiograms (ECGs) [40], diagnose myocardial infarction [41], and predict the prognosis period following cardiac surgery [42]. Nevertheless, they were criticized for lack of consistency and low specificity [21]. However, recent breakthroughs in the second-generation AI method called "Deep Learning" has made it much more potent and effective than earlier applications [43,44]. In recent years, AI's scientific applications have proliferated into image analysis, drug discovery, prediction of gene mutation, chronic disease management, etc. [45].

Diagnostics has been traditionally one of the major thrust areas of AI in medicine [46]. It is widely agreed that AI is likely to fundamentally transform the diagnostic and predictive analysis of medical images in the coming years [17,47]. Research in pathology and dermatology has already demonstrated AI's capability paralleling or outperforming their human counterparts in accurately detecting and classifying various types of cancer [48-50]. In radiology, computer-aided diagnosis (CAD) has been used in the detection of breast cancer on mammograms, differential diagnosis of lung nodules, and interstitial lung disease on CT [51]. Although speculations of fully automated diagnostics are looming, at present, it can only be said that AI algorithms could establish themselves as virtual "second readers" in various subspecialties of medicine [52].

In the past 4 years, there has been a surge in AI-based medical applications from across the world [3]. Several offerings are pursuing regulatory approvals to market their products [3,53]. Viz.ai for CT stroke diagnosis, iCAD's ProfoundAI for digital breast tomosynthesis, Algorithm for CT brain bleed diagnosis by AiDOC and Maxq.ai, breast cancer detection software Transpara by Screenpoint medical, and liver and lung cancer diagnosis using MRI or CT by Arterys are few of very popular commercially available Food and Drug Administration (FDA)-approved AI solutions in the US market [3]. In China, major hospitals have started using ICDDSS developed by Tencent Miying to assist physicians in screening for early lung and esophageal cancer [54]. Besides these, several other ICDDSS from Europe, China, and Japan are commercially available [55].

2.1.2. AI developments in the Indian healthcare sector

Global Tech giants are playing a key role in driving AI applications into healthcare practice in India [56]. IBM introduced the idea of AI in healthcare in India with the launch of its cognitive platform, Watson for Oncology [57]. Another example is Microsoft's partnership with Apollo Hospitals to develop an AI-powered risk score application designed for predicting the risk of cardiovascular disease [58]. Microsoft has also jointly developed AI-based ophthalmology screening devices in partnership with Forus Health and L V Prasad Eye Institute [59]. Google has also joined the race by developing AI-based solutions to detect the causes of preventable blindness in collaboration with Aravind Eyecare Hospitals [60]. In the area of clinical imaging, an Indo-US startup Qure.ai has developed FDA-approved automated screening algorithms for head CT, chest X-rays, and tuberculosis detection [61]. Their algorithms are offered over the cloud for a fee of $1–$5 per scan. It has already deployed products in over 50 locations in more than a dozen countries across the world [62]. Apollo Hospitals and Zebra Medical Vision, a popular Medical AI company, have announced a collaboration that focuses on deploying deep learning algorithms for the detection of 40 major conditions, including brain bleeds in head CT, cancer in mammograms, and critical conditions in chest X-rays [63]. GE Healthcare has started offering ML algorithms as smart subscription services through its newly launched AI platform Edison, as upgrades to its existing machines. It is also rapidly incorporating AI analytics capabilities in its new range of devices [64]. In addition, there are promising home-grown startups like SigTuple, Artelus, ChironX, and Niramai, offering a range of AI-powered diagnostic solutions [56]. Teleradiology companies have also started providing AI analytical capability as an add-on service [56]. India's public think tank "NITI Ayog" has recently released a white paper outlining the government's official strategy for the development of AI with a significant boost in the research funding for healthcare AI [62].

2.2. Clinical decision support system

A CDSS is a health information technology (HIT) that is developed to assist with clinical decision-making tasks for physicians and other healthcare professionals. According to Osheroff et al. [65], such CDSS technology "provides clinicians, staff, patients, and other individuals with knowledge and person-specific information, intelligently filtered or presented at appropriate times, to enhance health and health care." Perreault and Metzger [66] proposed the classification of CDSS using several dimensions, e.g., based on the timing at which they provide support, how active/passive that support is, etc. An important typology categorizes CDSS into knowledge- and non-knowledge-based systems (those with knowledge bases and those without) [16].

Knowledge-based CDSS typically use a knowledge base and a reasoning engine (formulas for combining associations in the knowledge base with actual patient data) while, non-knowledge-based CDSS uses ML and other advanced AI techniques (e.g., deep learning), which allow computers to learn from past experiences and/or identify patterns in clinical data [16]. While knowledge-based CDSS depend on if–then rules and an expert clinician's input for arriving at a diagnosis, its non-knowledge-based counterpart eliminates the need for writing rules and expert input [16]. Non-knowledge-based CDSS arrives at a diagnosis based on past experiences and known results. However, it suffers from a disadvantage that ML-based systems cannot explain the reasons behind their conclusions [16]. Further, knowledge-based CDSS typically covers the diagnosis of many different diseases, while non-knowledge-based CDSS focuses on a narrow list of symptoms for a particular disease [16].

Although there was active development in the field of CDSS since the 1970s, research on the adoption of CDSS followed much later [20,35,67]. A pioneering study on CDSS adoption conducted by Sambasivan et al. [67] identified "perceived threat to professional autonomy" and "physician's involvement in planning, design, and implementation" as significant predictors of their usage intentions. Shibl et al. [35] investigated the general practitioner's (GP) motivation to use CDSS (knowledge-based). They used a qualitative approach to extend the Unified Theory of Acceptance and Use of Technology (UTAUT) model by incorporating the new construct "trust in the knowledge base" [35]. A bibliometric review of CDSS research suggests that despite showing the evidence for usefulness, CDSS adoption has remained very low [68].

Our review of the literature suggests that most of the earlier studies have focused on the adoption of knowledge-based CDSS. Specifically, studies on the adoption of non-knowledge-based CDSS in medical diagnosis are missing from the literature and have only started to emerge very recently. Unlike knowledge-based CDSS, non-knowledge-based systems are highly autonomous (does not require an expert input) and are equipped with automated learning capabilities, such as neural networks, genetic algorithms, and other advanced forms of AI for deriving hidden associations from the patient data [16]. Further, they play a crucial role in aiding diagnostic decision-making as they are usually more sophisticated and accurate compared with their knowledge-based counterparts (eliminate expert human involvement and reduce errors) [16]. Therefore, psychosocial barriers, such as a threat to a physician's professional identity and fear of being replaced by technology tend to get intensified in the context of this technology [23,32]. However, despite their performance and accuracy, as non-knowledge-based systems cannot explain the reasons for their conclusions [16], most clinicians tend to resist using them. Hence, recognizing the gap in the literature with respect to non-knowledge-based CDSS, we focus on ICDDSS, a specialized form of non-knowledge-based CDSS used in providing diagnostic support to clinicians [16]. In the following section, we review the studies specifically related to the adoption of ICDDSS.

2.3. Prior research on ICDDSS adoption

Research on individual-level technology adoption is one of the most established and widely researched streams of IS research [69]. Researchers have proposed and tested several models, such as the technology acceptance model (TAM), UTAUT, etc. for explaining the user acceptance and use of technology [70]. We explored the prior research related to the ICDDSS adoption to understand the knowledge gaps in the literature. The result of our review is summarized in Table 1. We observe that despite growing interest in ICDDSS, there is a lack of research pertaining to the adoption of ICDDSS. Out of the five available studies, the majority [23,36,71] are qualitative/conceptual in nature. Only two studies have tested empirical models using quantitative methods [22,32]. The extant studies have employed both qualitative and quantitative research methods, such as surveys [22,32,71], vignette-based interviews [23] for studying the adoption behavior. The studies have examined perceptions of different groups within the healthcare setting, e.g., specialist doctors [71], medical students [23,32], and healthcare professionals in general (doctors, nurses, technicians, etc.) [22].

In terms of the theoretical underpinning, two out of five studies have focused on extensions of the UTAUT framework [22,36]. Panicker et al. [36] proposed the inclusion of "technological trust" into the UTAUT framework to account for the black-box nature of ICDDSS. Another study [22] tested an integrated model combining theoretical paradigms of UTAUT, task technology fit, and trust to predict the healthcare professionals' intentions to use ICDDSS. Studies from Germany have examined the consequences of the ICDDSS adoption using the theoretical lens of identity theory [23] and a combination of ambivalence and status quo bias (SQB) theories [32]. The other remaining study [71] was exploratory and descriptive in nature without any theoretical basis.

Further, in terms of results, Fan et al. [22] validated the impact of factors, namely, performance expectancy (PE) and initial trust, on ICDDSS adoption intention. The other factors in the study: effort expectancy (EE), social influence (SI), and perceived substitution crisis, had a non-significant influence on intention to adopt. Although Maier et al. [32] tested the impact of physician's ambivalence on their "resistance to change," but the study did not investigate the determinants of ICDDSS adoption. The remaining conceptual/qualitative studies highlighted the need to investigate the role of technological trust

Table 1
Summarized literature review on ICDDSS adoption.

Authors (Country)	Year	Context	Theoretical Underpinning	Methodology	Key Findings	Comments/Gaps
Panicker et al. [36] (India)	2016	Clinician's acceptance of ICDDSS for tuberculosis	UTAUT and trust theory	Conceptual	Proposed an extended UTAUT model incorporating "Technological Trust" to predict the use of automated diagnostic systems for tuberculosis.	Does not validate the proposed model empirically. Highlighted the need for future studies to include "Technological Trust" as a critical variable while studying ICDDSS adoption.
Fan et al. [22] (China)	2018	Healthcare professional's (doctor, nurse, technician, etc.) adoption of ICDDSS	UTAUT, task technology fit, trust theory	Quantitative - Survey: (n=191)	Initial trust mediates the relationship between UTAUT factors and behavioral intentions. Perceived substitution crisis has no impact on the behavioral intention to adopt.	Not entirely from a physician's point of view, the sample comprises other respondents, such as nurses, technicians, etc. Focused only on the positive drivers of adoption and did not examine the effect of physicians' resistance and its reasons. Could not establish the relationship between perceived substitution crisis and intention to use.
Jussupow et al. [23] (Germany)	2018	Physician's adoption of ICDDSS	Identity theory	Qualitative vignette-based interviews (n=182)	Explored the process of professional identity construction triggered by ICDDSS adoption and its possible behavioral consequences	Findings from this "research in progress" paper suggest that ICDDSS can be perceived as a threat to professional identity by physicians and could potentially become an object of physician's resistance; Does not provide a conceptual or empirical model to examine ICDDSS adoption.
Maier et al. [32] (Germany)	2019	Physician's adoption of ICDDSS and its consequences	Ambivalence and SQB theory	Quantitative survey (n=74)	Physician's ambivalent attitude towards ICDDSS leads to a preference for status quo and development of resistance to change	Does not directly investigate the factors influencing the adoption of ICDDSS. It highlights the role of "resistance to change" in explaining ICDDSS adoption behavior.
Sarwar et al. [71] (Multi-country)	2019	Physician's perception about the use of ICDDSS in pathology	NIL	Qualitative survey (n=487)	Respondents believed that AI could facilitate improvements in workflow efficiency and quality assurance. Identified concerns, such as the potential for job replacement, legal implications, and the need for physician training.	Does not provide a conceptual or empirical model to examine ICDDSS adoption. No theoretical underpinning. Suggests the importance of concerns, namely, job replacement, legal issues that could play a role in the adoption decision.

and concerns such as job replacement, legal implications, the threat to professional identity, and other antecedents of resistance to change in determining ICDDSS adoption [23,36,71].

Our review of the literature on the adoption of ICDDSS revealed several issues and gaps. First, despite many ICDDSS being commercially available in the last few years, there is a paucity of research on this topic [19]. The available studies are fragmented in terms of methodology, theoretical foundation, and focus, and do not provide an understanding of the comprehensive set of factors that explain the ICDDSS adoption by the main stakeholder group, the medical practitioners. Second, the prior research on the adoption of similar technologies, such as knowledge-based CDSS or earlier versions of non-knowledge-based CDSS, may not be relevant to adoption of the AI-based ICDDSS due to its unique characteristics, such as (1) superior accuracy paralleling/exceeding human experts, (2) autonomous decision-making ability which does not require expert human input, 3) self-learning ability—the ability to automatically identify associations from the clinical data, and (4) black-box nature of the algorithms—inability to explain the reasons for their conclusions [30,31]. These unique features of ICDDSS raise concerns, such as physicians' threat to professional identity, threat of replacement, apprehensions of dependency, patient safety, and concerns about the legal liability of misdiagnosis. All these unique issues make the context of ICDDSS adoption different from that of the earlier studies.

Third, although a prior study [23] provides a cue regarding the presence of physician's resistance and lists it as a possible outcome of physician's perceived threat to professional identity, it did not validate the proposition. Similarly, Maier et al. [32] probed the relationship between physicians' ambivalent attitude about ICDDSS and "resistance to change." However, it did not probe into other antecedents of "resistance to change" or its impact on the intention to use. Thus, we observe that resistance research in the context of ICDDSS is largely unexplored [32]. Moreover, recent research on challenges of AI adoption in public healthcare [33] and an opinion paper [34] has identified user resistance as a key barrier to its adoption. We observe that there is a void when it comes to an understanding of what factors contribute to user resistance in the context of ICDDSS, which requires further investigation.

Fourth, prior studies on ICDDSS have examined only the positive drivers of adoption and did not probe into the role of inhibitors in the adoption decision-making. From the literature, it is evident that concerns, such as the threat of replacement, legal liability, etc. could inhibit the use [71]. Cenfetelli [72] has argued that extant theories on IS adoption and usage has exclusively focused on positive (enabling) perceptions while ignoring the negative (inhibiting) perceptions that may impede the adoption. He proposed a dual-factor theory (DFT) to integrate both enabling and inhibiting perceptions driving adoption behavior in an integrated framework. Moreover, empirical evidence shows that negative perceptions inhibit the adoption/usage [26-28]. This prompted us to turn to DFT as a general overarching theoretical framework for studying ICDDSS adoption.

Finally, while ICDDSS adoption is valuable in developing countries, such as India, given their highly skewed doctor–patient ratio, adoption is very low [56]. Moreover, there are no studies evaluating the perceptions of medical practitioners from developing countries in general. Additionally, since India is a collectivist society, SI may play a significant role in enhancing ICDDSS adoption [73,74]. Furthermore, in India, there is no legal framework to decide on the accountability of medical malpractice/negligence caused due to ICDDSS [75]. Therefore, the adoption of ICDDSS in the Indian context is unique in nature and requires special investigation.

2.4. Dual-factor theory

The DFT of IS use argues that considerations of IT use by the potential users are based on simultaneous consideration of enabling and inhibiting factors [28,72]. According to Cenfetelli [72], enablers are factors that encourage adoption, and inhibitors are those negative factors that, when present, inhibit IT use, but do not necessarily favor use when absent. This asymmetric effect implies that inhibitors are not quite the opposite of enablers; rather, they are qualitatively different constructs that are independent of enablers, but may coexist with them [28, 72]. Empirical research also indicates that enabling and inhibiting perceptions have different antecedents and consequences, implying that they are conceptually distinct [26-28]. Further, DFT is a well-accepted theory that has been applied in different contexts, such as healthcare IT resistance [26-28], non-adoption of technological innovations, [76] etc. In the context of healthcare IS, Bhattacherjee and Hikmet [28] used DFT to explain physicians' resistance to healthcare IT. For the current study, we have invoked the DFT because it is expected that analyzing both enablers and inhibitors together would provide a comprehensive understanding of the response of medical practitioners to ICDDSS. Thus, the DFT of IS use provides a theoretical bridge that connects IT usage and user resistance in an integrated framework.

2.5. User resistance to technology

User resistance is one of the most significant factors associated with the failure of IT projects [29]. IS research has offered rich insights into why people adopt/use technologies but, individuals' resistance to technologies has received much less attention so far [77]. This line of research has contended that user resistance cannot be considered simply as the opposite of acceptance [72,77]. Early thoughts on the notion of user resistance are credited to Lewin's [78] study on opposing forces. Lewin [78] argued that social systems, like biological systems, tend to preserve the status quo by resisting change and reverting back to the initial state, a phenomenon known as "homeostasis."

In the IS literature, only a few studies have tried to open the black box of user resistance and provide a theoretical explanation of why it occurs [77]. Markus [79] postulated that user resistance arises from the change in intra-organizational power distribution with the introduction of the new IS. Accordingly, a loss of power can lead to resistance by users. Joshi [80] used the perspective of equity theory to analyze resistance to change related to IS implementation. She suggested that users would evaluate every change in terms of its impact on their equity status, and resistance could occur if the net gain is negative. Oreg [81] introduced the concept of dispositional resistance to change and argued that individuals have a trait resistance linked to their personality, which makes them resistant to change in specific settings. Lapointe and Rivard [82] found that a perception of threat arising from the interaction of object of resistance (system features) and initial condition results in the resistance behavior (active or passive).

Bhattacherjee and Hikmet [28] developed a model of physician resistance of healthcare IT by integrating technology acceptance and resistance literature using DFT of IT use. They argued that resistance was a generalized opposition to change caused by the anticipated adverse consequences of change. In other words, why people resist technology is not in the technology itself, but the change brought on by the introduction of the IS in the workplace [28]. They described "resistance to change" not as behavior, but as a "cognitive force precluding potential behavior" (an antecedent of adoption behavior). The model explains resistance through a perceived threat lens, which is based on earlier research [79,82]. Even though the perceived threat was identified as the only predictor of user resistance (resistance to change) in the model, they urged researchers to identify additional predictors. This view was further strengthened by Kim and Kankanhalli [83], who developed a behavioral measure of user resistance and used the theory of SQB to explain the user resistance prior to the implementation of a new IS.

Thus, the IS research has examined the user resistance at three different levels as a behavior (passive or active, overt or covert) [83], perceptual resistance to change (inhibiting perception about change to the status quo) [28], and dispositional resistance to change (personal proclivity to oppose a change in general) [81].

3. Methodology

The current study uses a mixed-methods approach to qualitatively identify the factors that enable and inhibit the adoption of ICDDSS, followed by a quantitative survey-based study that empirically tests the influence of the identified factors on ICDDSS adoption intentions [37, 84]. A mixed-method design was chosen as it helps to explain the phenomenon in greater depth and detail using the complementary strengths of qualitative and quantitative approaches [37,84]. Following the guidelines for conducting the mixed-methods research [37,84], the current study uses a qualitative study based on netnography and interviews followed by a quantitative study using a survey instrument. In sections 3.1 and 3.2, we refer to the qualitative research as study 1 and quantitative research as study 2. Further, study 1 is conducted in two stages, namely, (1a) that refers to the netnography method and (1b) that refers to interview-based study.

3.1. Study 1: Qualitative research—netnography & interviews

Our qualitative study sought to answer the research questions RQ1 and RQ2. To answer these questions, we first used a netnography method [85] to gather data regarding medical practitioner's perceptions about using ICDDSS (study 1a). Netnography, often known as "online ethnography," is a relatively new method of conducting exploratory research that uses ethnographic research techniques tailored to the study of online communities [86]. In netnography, information available in various online forums is used to understand user/consumer behavior and factors affecting their decision-making [86]. Netnographic approaches may be used to conduct research either by actively integrating community members or passively observing the community and integrating the gathered information shared by the members [85]. As a method, it is faster, easier, and less expensive than traditional ethnography and more naturalistic and unobtrusive (avoids researcher—subject interaction bias) than focused groups or interviews [85]. Further, it can be used both as a standalone method and in combination with other methods to provide rich, deeper insights into the phenomenon [85].

Following the netnography method [85], we used comments posted against relevant discussions related to ICDDSS in radiology on one of the world's most popular discussion forums meant for radiologists, namely, Auntminnie.com. We used keywords such as "Artificial Intelligence," "AI," "AI diagnostics," "AI in radiology," and "Machine Learning" to search for discussion threads related to ICDDSS in radiology. This yielded a total of 23 discussion threads relevant to the research theme, posted from the year 2016–2019. These threads were extracted using a web scraper tool. The scraping process yielded a total of 1,814 comments posted by 187 radiologists amounting to 1,80,252 words. After a thorough screening and removal of irrelevant comments, a total of 289 comments amounting to 35,101 words posted by 89 radiologists were found useful for further analysis.

The netnography was followed by an in-depth interview-based study referred to as (1b). We interviewed 15 doctors from India specialized in radiology and imaging identified through purposive sampling. Appendix A provides an overview of interview data sources. All the respondents were active medical practitioners with knowledge about ICDDSS and its functionality. The interview followed a semi-structured format, and questions broadly focused on the enablers and inhibitors of the use of ICDDSS in the clinical practice. Interviews lasted from about

30 min to 1 h and were conducted in English. All the interviews were voice recorded and transcribed for further examination.

We used thematic analysis [87], a well-established qualitative data analysis method, to analyze the data collected using netnography (1a) and interviews (1b). Thematic analysis is a qualitative data analysis method that helps in "identifying, analyzing, and reporting patterns (themes) within the data" [87]. In this method, data are not quantified; instead, implicit themes are identified through a coding process [87]. We followed a hybrid approach based on both deductive and inductive coding techniques to arrive at the thematic codes [88]. Deductive codes were inferred from the related literature, while the inductive codes were derived from the data. A qualitative data analysis software, QSR NVivo version 10, was used to assist the coding process. Sensitized by the review of related literature, we carefully reviewed the whole data and developed a dictionary of codes by identifying the repetitive themes in raw data. Based on this dictionary, two authors coded 100 randomly selected comments together, discussed disagreements, and refined the codebook. The rest of the codes were generated independently by the two researchers. The overall rate of agreement Cohen's kappa (κ) was 88% (> threshold value = 0.80), suggesting good reliability [89]. Finally, the coding differences were discussed to reach a consensus. After the open coding process, we reanalyzed the codes to identify common themes based on the shared meaning and relationships between them. Open codes were then collated into matching themes [87]. A summary of the themes and subthemes that emerged from the analysis along with corresponding excerpts is presented in Appendix B.

Our thematic analysis of the data revealed the role of various enabling and inhibiting factors that influence ICDDSS adoption intentions (see Appendix B). Among the enabling (positive) factors, we identified two major themes, namely, PE, and trust in ICDDSS. Under the broad theme of PE, respondents' beliefs on how ICDDSS would aid them in improving their job performance is summarized. The subthemes related to respondents' trust in the ICDDSS theme consist of medical practitioners' trust in ICDDSS technology and training methods, explainability, skepticism about purpose and claims of AI, and the need for more scientific evidence. With respect to the negative (inhibiting) factors, the user resistance to ICDDSS emerged as the prominent factor/theme. Under the theme of user resistance, respondents expressed their resistance to the potential changes in clinical practice due to the introduction of ICDDSS.

Additionally, the thematic analysis also revealed the likely reasons for resisting the change related to the introduction of ICDDSS to clinical practice; they are summarized under the themes, perceived threat, medico-legal risk, and performance risk. With respect to the perceived threat, respondents expressed their threat of being replaced by machines or by doctors from other specializations assisted by AI, the threat of losing autonomy, deskilling, and decline in pay. The theme medico-legal risk consists of subthemes that summarize the risk of malpractice litigations/legal liability of the doctor and the concern that ICDDSS vendors will evade legal accountability through conditional clauses. The theme performance risk consists of respondents' concern about the risk of ICDDSS failure/malfunction, errors, and maturity of the technology for clinical use. The factors and the relationships that emerged from the qualitative study were further used in the conceptualization and operationalization of the research model tested in study 2 (quantitative stage) of this study.

3.2. Study 2: Quantitative research – surveys

In this stage, we used a quantitative survey to empirically examine the relationships between factors identified through the synthesis of literature and qualitative study (study 1). A research model (see Fig. 1) was developed by combining the insights from literature and study 1 to explain the medical practitioner's intention to use ICDDSS. The following sections describe the hypotheses development and the method followed in collecting and analyzing the data.

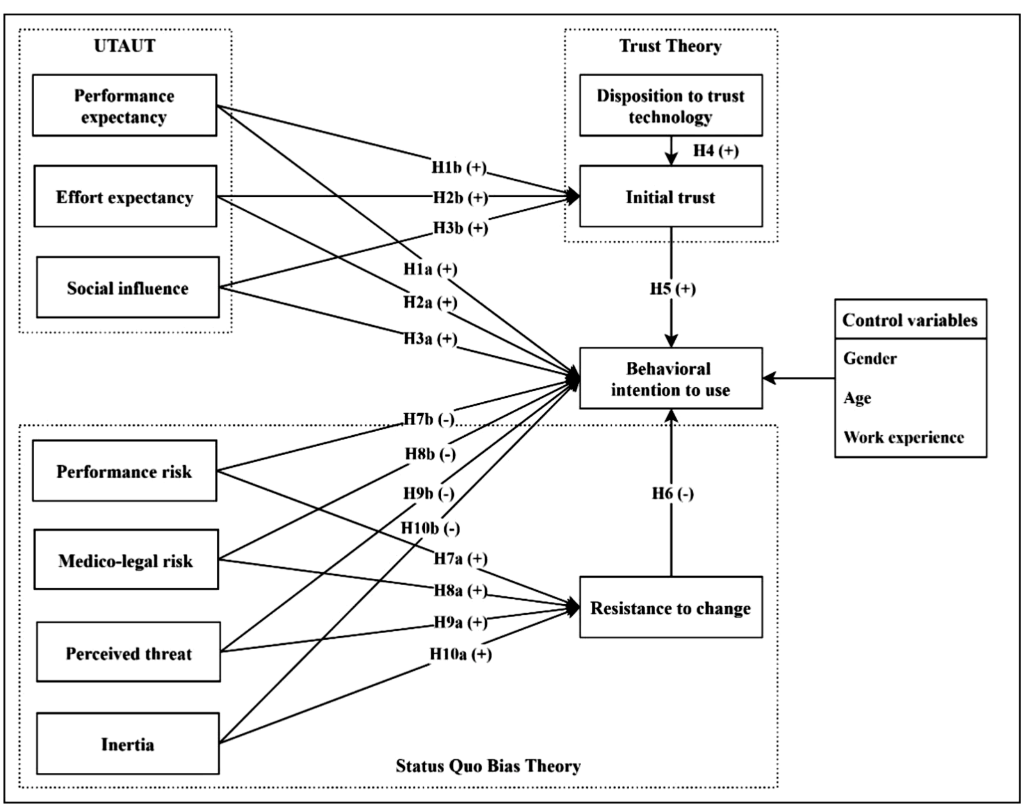

Fig. 1. Research framework.

3.2.1. Development of hypotheses

In developing the research model, we followed a three-layered approach: (1) use of DFT as the overarching theory to understand both the enabling and inhibiting factors affecting the medical practitioner's intentions to use ICDDSS [28,72]. (2) Use of qualitative data to identify the context-specific enabling and inhibiting factors that influence the adoption intentions. (3) Use of complementary insights from the literature review and qualitative data analysis to identify relevant theoretical lenses and develop the hypotheses. The final dependent variable of this research is the medical practitioner's behavioral intention to use (BI) ICDDSS. Behavioral intention to use is a strong determinant of actual usage in IS usage literature [69,70,90]. In this research, as we are dealing with a pre-adoption setting, we intend to limit our discussion to potential user's "intention to use" than actual usage. Further, the insights regarding the factors and their potential relationships identified in the qualitative study (see Table 2) were used to identify the theories for developing the integrated research framework.

Accordingly, UTAUT, technology trust theory, and SQB theory were found relevant to our study (see Table 2). Thus, based on the DFT framework, we propose that the medical practitioner's intention to use ICDDSS systems is based on two opposing forces: enabling and inhibiting perceptions [28,72]. Based on relationships identified in the qualitative study, we use the UTAUT and technology trust theory to model the enabling perceptions. Factor "performance expectancy" and "Trust in ICDDSS technology" belonging to UTAUT and technology trust theory, respectively, were identified through the qualitative study. In addition, we included two other enabling factors from the UTAUT [35,70,97] which could influence BI, namely, EE and SI. According to UTAUT, PE, EE, SI, and facilitating conditions (FC) determine intention to use technology [70]. However, FC was deemed irrelevant for this study since FC becomes insignificant in explaining the intentions in a pre-implementation context [98]. Empirical evidence also suggests that FC directly affects the actual use and not the intentions [70].

Again, from the qualitative study, it was evident that resistance to change is the key inhibiting perception that has a negative influence on BI. This is in line with the prior literature on HIT use that identifies resistance to change as the key inhibiting factor that influences physicians' intention to use HIT [28]. Further in their research, resistance to change was primarily driven by perceived threat (i.e., physician's perceived loss of control over their work due to adoption of ICDDSS). We extend the antecedents of resistance to change by combining the insights from the qualitative study (see Table 2) and the theoretical perspective of SQB [95]. Accordingly, we identified four potential antecedents of medical practitioner's resistance to change, namely, perceived threat, medico-legal risk, and performance risk from the qualitative study. The construct inertia was identified from the literature as an important determinant of resistance to change [26,95,99]. We develop the hypotheses in the following paragraphs.

According to UTAUT, PE is conceptualized "as the degree to which an individual believes that applying the technology will help him or her to attain gains in job performance" [70]. In the context of healthcare IS, if medical practitioners believe that new technology is more effective and beneficial to their clinical practice than the existing methods, they will be motivated to use and accept it [100,101]. This was echoed in our qualitative study as well. For example, one of our interviewees (R10) remarked that "It can increase the productivity by 40–50% something that you do across 8 hours can be now done in 4–5 hours". He went on to state that if doctors are able to see that ICDDSS can help improve their accuracy and speed in diagnosis and help free them up from mundane tasks, they will be more likely to have a positive attitude towards using it. Therefore, we argue that if the practitioner believes that using ICDDSS will help improve his/her job performance (i.e., improve the speed, accuracy, productivity, and reduce the workload), then he/she will be more likely to develop an intention to use it. Therefore, this study proposes the following hypothesis:

Table 2
Summary of relationships identified in the qualitative study (study 1).

RQ	Relationships identified in the qualitative study	Sample excerpts from the qualitative study	Related theory in literature	Supporting literature
RQ1	PE has a positive influence on the intention to use ICDDSS	*"I'd love to use this […] if we have this technology which would allow us to filter normal scans from the abnormal, the time spend by the radiologists will be reduced*" [R13]	UTAUT [70]	[70]
	Trust in technology has a positive influence on the intention to use ICDDSS	"*I am willing to use it, but here are two problems. If I can't always trust the 'diagnostic decisions' rendered by AI, then I have to double-check all of its work […] I blindly trust the read by the AI, and something bad happens with complex technology is the AI company paying for the liability?*" [N1]	Technology trust theory [91]	[22,24,35, 36,91-94]
	Resistance to change has a negative influence on the intention to use ICDDSS	"*machine doing reporting is not acceptable right now […] I'm not keen on using it as of now.*" [R8]	SQB theory [95]	[26-28]
RQ2	Perceived threat has a positive influence on resistance to change	*"I'm not in favor of AI-based diagnostics. […] people like me trained in radiodiagnosis are worried if this could make our jobs redundant. I'm worried once the technology matures, whatever we have learned over the years may become obsolete."* [R12]	SQB theory [95]	[28,79]
	Medico-legal risk has a positive influence on resistance to change	*"if there is an issue and the patient sue you, where are you going to stand? I am surprised that in the US, they are working on it without addressing the medico-legal part. It won't be that easy in India; there will be opposition."* [R11]	SQB theory [95]	[96]
	Performance risk has a positive influence on resistance to change	*"AI, even if it's a 99.99% approximation of a human imager, are prone to catastrophic errors with a wholly unacceptable failure mode, and that's what make it unacceptable for mission critical environment […] this is not acceptable in the health care setting*" [N39]	SQB theory [95]	[95]

Notes: RQ, Research Question; UTAUT, Unified Theory of Acceptance and Use of Technology; DFT, Dual-Factor Theory of IS use; SQB, Status Quo Bias.

H1a. . PE has a positive impact on the medical practitioner's intention to use ICDDSS.

According to the UTAUT model, EE is defined as "the extent of ease associated with the use of a system." [70]. Perceived ease of use was identified in the literature as a factor facilitating the use of CDSS [102]. It is believed that an easy to use system would be more likely used than one that is complicated [103]. Therefore, in the context of ICDDSS, we expect that if the doctors perceive the ICDDSS to be simple and easy to operate, they will be more inclined to develop an intention to use it in their medical practice. Thus, we formulate the following hypothesis:

H2a. . EE has a positive impact on the medical practitioner's intention to use ICDDSS.

The UTAUT viewpoint suggests that the user's perception of the opinion of others (peers, seniors, relevant others) regarding whether he or she should be using a target technology affects his or her intention to do so [70]. It is also observed that physicians often seek approval and validation from professional peer groups when it comes to the adoption of new and innovative means of practice [104-105]. Moreover, the salience of SI in facilitating physician's adoption of HIT is highlighted in recent research by Lu et al. [97]. Thus, we believe that the medical practitioner's intention to use ICDDSS could be influenced by the opinion of people in their social and professional circles. This effect would be even more pronounced in the context of a collectivist society, such as India [73,74]. Hence, we suggest the following hypothesis:

H3a. . SI has a positive impact on the medical practitioner's intention to use ICDDSS.

Trust in ICDDSS technology is another key enabler that was identified in the qualitative stage (study 1). Research in IS and human-computer interactions (HCI) have described trust as a key determinant of technology usage [92,106]. The idea of trust has its origins in organizational behavior and is defined as "the willingness of a party to be vulnerable to the actions of another party" [107]. Empirical evidence suggests that trust does not essentially develop steadily over time [108]; instead, trust at different phases are shaped based on a distinct set of factors and processes [109]. For example, if the trustor has no prior direct interaction with a trustee, he/she will not be able to develop trust-based on first-hand knowledge of the trustee. In these situations, the trustor will rely on other sources, such as second-hand information, personal instinct, or contextual factors, to infer trust [91]. McKnight et al. [110] defined this idea of "trust in an unfamiliar party" as initial trust. Li et al. [92] extended the concept of initial trust to the IS setting and emphasized its role in technology adoption. Because most medical practitioners in India have no prior experience in using ICDDSS, in this research, we limit our discussion to the initial stage of trust formation in technology.

Gefen et al. [93] argued that PE and EE would have a significant influence on the trust formation process. Studies that followed have found evidence of the influence of PE and EE on the initial trust in the context of health wearables [111] and telehealth [112]. Extrapolating this to the context of ICDDSS, when medical practitioners have high expectancies regarding the performance of ICDDSS, they are likely to have higher confidence and trust. Similarly, the perception of difficulty in using ICDDSS is expected to reduce the confidence in the reliability of the device and thereby reduce the trust in the advice given by the system. In other words, higher perceived ease of use may improve user confidence in the system. Moreover, an earlier study [113] on healthcare IT has reported the positive linkage between EE and Trust. On these grounds, we propose the following hypotheses:

H1b. . PE has a positive impact on the medical practitioner's initial trust perception.

H2b. . EE has a positive impact on the medical practitioner's initial trust perception.

In the absence of direct interaction with the system, trust formation is dependent on their experiences with other systems, their knowledge about similar systems used in other contexts, and/or others' views about the system [92]. ICDDSS is an emerging technology, and most medical practitioners do not have any direct experiences with it; in this setting, practitioner's perception about important other's opinion (particularly the senior practitioner's, professional body's, organizational leader's and colleague's opinion) about using ICDDSS would significantly impact the initial trust formation. However, it is likely to change once they start using it. Additionally, prior research in IS also supports a direct relationship between SI and trusting beliefs [92]. Hence, we propose the following hypothesis:

H3b. . SI has a positive impact on the medical practitioner's initial trust in ICDDSS.

Disposition to trust technology (DT) is "the extent to which a person displays a tendency to be willing to depend on technology across a broad spectrum of situations and technologies" [94]. Depending upon the level of DT, some people are more likely to trust technology than others, while some might be very skeptical. While not specific to clinical practice, individual differences in cognition, cultural background, and personality can also affect an individual's DT [114]. From the organizational context, the disposition to trust is found to influence how much trust one has for others before having any interaction [107], and this is most influential in the early stages of a relationship [115,116]. Hence, we believe that disposition to trust is likely to enhance medical practitioner's initial trust perceptions of ICDDSS positively. Therefore, we propose the following hypothesis:

H4. . DT has a positive impact on the medical practitioner's initial trust perceptions.

In the case of radically new technologies, initial trust assumes an essential role as the perception of risk and uncertainty needs to be overcome in order to develop a willingness to use these technologies [92,117]. Initial trust has been found to play a mediating role in the intention to adopt several technologies such as e-government services, mobile wallet adoption, wearables, and healthcare IT [22,118-120]. Given the risk to the health and life of patients, medical practitioners would tend to be more careful than technology adopters in other settings while intending to use ICDDSS in their routine clinical practice [22]. Our interviewees from the qualitative study (see Appendix B) also suggest the same, e.g., one of our interviewees (R13) says, "there will be some issues about the credibility of AI results […] It is just not that the machines say something and we are going to accept that." Adoption would require practitioners to trust ICDDSS despite the possibility of malfunction, misdiagnosis, and other adverse consequences resulting from the use, given the black-box nature of the algorithms [24]. Earlier research in the context of CDSS adoption also argues for the inclusion of trust in technology in predicting the adoption intention [22,35,36]. On these grounds, we propose the following hypothesis:

H5. . Initial trust has a positive impact on the medical practitioner's intention to use ICDDSS.

Through our qualitative study, we identified user resistance in its perceptual form (resistance to change) as the key inhibiting factor affecting the ICDDSS use intentions (see Table 2). Bhattacharjee and Hikmet [28] defined user resistance in the IS context as a "generalized opposition to change engendered by its expected adverse consequences." They further described it as a preference for the status quo and opposition to change introduced by the new IS [28]. The introduction of a new system is often accompanied by substantial changes in the existing work processes of the user [28]. In the context of ICDDSS, where the change is envisaged to be transformational (in a way that threatens the autonomy of the practitioners), in view of the natural human proclivity to resist change, users would tend to oppose the technology. For example, as one of our interviewees (R8) from the qualitative study remarked, “machine doing reporting is not acceptable right now […] I’m not keen on using it as of now.” Moreover, prior studies on HIT [26-28] have provided evidence for the negative impact of resistance to change on usage intentions. Furthermore, because of a desire to maintain the status quo, that is, resistance to change is particularly plausible in the pre-implementation phase [28]. Based on these grounds, we propose the following hypothesis:

H6. . Resistance to change has a negative impact on the medical practitioner’s intention to use ICDDSS.

We use the SQB theory [95] to explain the antecedents of resistance to change. The SQB theory explains the preference of individuals for maintaining their current status rather than switching to a new or potentially superior course of action [95]. From the rational decision-making viewpoint of SQB theory, the user may persist with the incumbent system if they perceive a psychological uncertainty associated with the change [95]. Our qualitative study (study 1) presented evidence regarding three manifestations of such uncertainty, namely, performance risk, the medico-legal risk associated with the use of ICDDSS, and the perceived threat of being outdated or replaced by ICDDSS. Further, the cognitive misperception viewpoint of SQB theory is also expected to play a role in inducing a preference for maintaining the status quo [99]. According to this view, practitioners may like to continue using their incumbent systems because of a habit or because it might be too stressful or emotionally strenuous to change (referred to as inertia) [99].

As mentioned earlier, one explanation of status quo bias is grounded in the presence of uncertainty in the decision-making setting. Uncertainty costs can be understood as the psychological uncertainty or perception of risk related to the performance of a new alternative (a new IS) [83]. It is known that performance risk increases the anticipation of adverse outcomes, resulting in an unfavorable attitude that typically results in a negative impact on the user’s intention to use the target technology [99,121]. Prior research has shown that uncertainty and risk perceptions produce unpleasant psychological reactions, such as anxiety [122,123]. Such reactions can influence the valuation of the potential change and induce SQB [123]. Our qualitative study also gives evidence for the presence of risk perceptions about the possible malfunction, false positives, etc. which were identified as the reasons for medical practitioners’ resistance to change (see Appendix B). Therefore, in case of uncertainty regarding the performance of the ICDDSS, medical practitioners would prefer to stick to the status quo and resist switching to a new system for diagnostic decision-making. Hence, we hypothesize that:

H7a. . Performance risk has a positive impact on the medical practitioner’s resistance to change.

Another major uncertainty involved in the use of ICDDSS in medical practice is related to the medico-legal implication of AI-aided/performed diagnosis. Our qualitative study offers a corroborative view, e.g., “If there’s an AI miss or wrong interpretation, is the AI company going to take all liability? They still want a radiologist to overread/sue.” (N75). Also, given the opaque nature of AI algorithms, implementation of ICDDSS raises complex legal questions regarding the liability of healthcare professionals vs. manufacturers, especially if they cannot explain the system’s recommendations [124]. Adding further to the problem, present laws in India are not clear on who bears the damages in the event of an injury or damage. Thus, any liability arising from an incorrect interpretation or misdiagnosis will ultimately be contingent upon the practitioner who signs the report and not on the software developer or the programmer who built the ICDDSS [75,96]. As the current legal frameworks are inadequate to address the realities of these innovations [96], doctors may not want to add to their medical malpractice risk by agreeing to change to a new way of practice using ICDDSS. Thus, the practitioners who perceive a high degree of medico-legal risk would prefer to stick to the current status quo and resist switching to the new way of practice using ICDDSS. Based on these arguments, we hypothesize that:

H_{8a}. Medico-legal risk has a positive impact on the medical practitioner’s resistance to change.

According to Bhattacherjee and Hikmet [28], people resist change if they expect it to have effects that threaten the status quo, such as potential power loss or loss of control over strategic resources. In this case, the prospect of using ICDDSS has given rise to concerns about the possible threat of replacement or loss of professional autonomy among the medical practitioners [46,125]. Our qualitative study identifies major dimensions of this threat (see Appendix B), such as the threat of being replaced by machines or doctors from other specialties (with the help from ICDDSS), loss of autonomy in the job, the threat of deskilling, and decline in pay. Earlier studies on CDSS have also identified “perceived threat to professional autonomy” as a determinant of its adoption [67,102]. Additionally, Fan et al. [22] assessed the impact of the “Perceived substitution crisis” on the adoption intentions among Chinese healthcare professionals, but the hypothesis was not statistically supported. Though the experts differ in their opinion about the possible doomsday scenario of a total replacement [126], there are growing concerns about the negative consequences of using ICDDSS [127]. Considering these arguments, we believe that perceived threats about deskilling, unemployment, and dependency will result in the formation of a negative attitude towards the intention to use ICDDSS and result in an increase in resistance towards it. On these grounds, we hypothesize:

H9a. . Perceived threat has a positive impact on the medical practitioner’s resistance to change.

The cognitive misperception perspective of SQB theory identifies the inertial tendency of the user of an incumbent system [95,99]. Users tend to persist in using the incumbent systems even when they know it may not be the best (efficient or effective) way to do a particular task, either because it may be too stressful to make a change or because it may be something that they have always done in the past or they have developed a strong emotional attachment to the current way of doing things [95]. Inertia is thus not merely the continuance of an incumbent course of action, but rather a preference to stay put even if there are better options and incentives to change [99]. Therefore, in the case of ICDDSS adoption, the medical practitioner’s tendency to continue with old practices and systems even in the presence of better alternatives is expected to contribute to the “resistance to change.” Consequently, we propose the following hypothesis:

H10a. . Inertia has a positive effect on the medical practitioner’s resistance to change.

The potential determinants of resistance to change, namely, performance risk, medico-legal risk, perceived threat, and inertia, may also directly influence the intention to use ICDDSS, in addition to their indirect influence through the resistance to change. The literature on DFT and inhibitors supports the negative impact of inhibitors on the usage intentions [27,72]. Further, resistance to change has been found to play a mediating role in behavioral intention to adopt several technologies such as HIT, new media technology, etc. [27,28,128]. Accordingly, we propose the following hypotheses:

H7b. . Performance risk has a negative impact on the medical practitioner’s intention to use ICDDSS.

H8b. . Medico-legal risk has a negative impact on the medical practitioner’s intention to use ICDDSS.

H9b. . Perceived threat has a negative impact on the medical practitioner's intention to use ICDDSS.

H10b. . Inertia has a negative impact on the medical practitioner's intention to use ICDDSS.

3.2.2. Survey instrument

A structured questionnaire was formulated to collect data to test the proposed theoretical model. To improve the reliability of the measurements, most of the constructs were adapted from pre-existing instruments based on prior research with minor rewording where necessary for the current research context. The items for the construct medico-legal risk were newly developed based on [96] and qualitative study (study 1). Similarly, two items in the construct perceived threat and one item in the construct performance risk were newly formulated based on the insights from study 1. To examine the face validity of the measurement instruments, one Professor of IS and two doctors specialized in radiology from a large private hospital in Mumbai, India, were invited to give suggestions. The survey instrument was modified by incorporating their recommendations. Further, before the actual study, the questionnaire was circulated to doctors specialized in radiology via an online radiology discussion forum. The objective of this pretest was to ensure clarity of the wordings in the questionnaire. A total of 24 radiologists completed the survey and gave feedback on the clarity of the questionnaire. The survey form was modified by including their suggestions. The final list of constructs used in this study, along with its corresponding items and sources, is provided in Appendix C. Additionally, to rule out the confounding effects of variations in the characteristics of the respondents which may influence their intention to use ICDDSS, we included them as controls in the framework. The control variables included were gender, age, and work experience of the respondents.

3.2.3. Study design, procedure, and participants

A popular national-level radiology training program was chosen for the data collection. Access to the training program and permission for data collection was obtained from the organizers a priori. The training program also included an in-depth session on applications of AI in radiology led by a domain expert (a professor of radiology who is an active researcher in the area of AI in radiology). We believe such an arrangement ensured adequate awareness among the respondents about the developments in the emerging area of AI in radiology.

To further enhance the understanding of the respondents on commercially available ICDDSS, four strategies were followed by the researchers. On the first day of the training program, after the session on the use of AI in radiology was completed, (1) a detailed list of commercially available ICDDSSs along with their links, and product videos were circulated via email and a mobile app meant for the training program. (2) An online quiz competition based on the information circulated was announced to motivate the participants to gain more information on ICDDSS. (3) Product demonstration videos of the commercially available ICDDSSs were displayed during intervals between the training sessions. (4) Before the data collection, a live demonstration of an ICDDSS application for chest X-rays and mammography named Lunit insight [129] was arranged to give the participants deeper insights into the functionality of ICDDSS. After that, participants were provided an online link to the ICDDSS via email and were encouraged to try it on their own.

Following this, participants were briefed about the context and the purpose of the study. Participants were given both paper-based and online version of the questionnaire and were asked to submit the filled forms on the last day of the program. They were specifically instructed to fill the questionnaire based on their idea of the general collection of ICDDSS rather than any product in particular. The name of no particular ICDDSS was mentioned in the questionnaire. No incentives were provided for filling the questionnaire. Participation in the survey (anonymous) was voluntary, and informed consent was obtained from the participants. Filled questionnaires were collected back with the help of volunteers. Email reminders were sent to facilitate the submission of the forms. Out of 300 registered participants and 20 other doctors, including organizers and educators of the training program to whom the questionnaire was sent, a total of 218 (162 paper and 56 online) chose to respond to the survey. After filtering out incomplete and evidently random responses, a total of 183 filled questionnaires were found complete in all respects and usable for further analysis. The response rate was thus 57.18% for the overall questionnaires sent.

4. Data analysis and results

4.1. Respondents' profile and characteristics

The respondents' demographic characteristics presented in Table 3 reveal that most of them were male (63.93%) and younger than 40 years of age (82.51%). In terms of work experience, 63.93% of the respondents had experience ranging from 0 to 5 years. Another 27.87% of the respondents belonged to category 5–20 years. Medical practitioners with more than 20 years of experience were less (8.2%) in the sample. In terms of title, most of them (57.92%) were resident radiologists, followed by consultant radiologists (34.97%); the rest of them were radiologists in academic roles.

4.2. Structural equation modeling analysis

The study used the partial least squares-structural equation modeling (PLS-SEM) approach to test the hypotheses. Hair et al. [130] have recognized this technique as a prediction-oriented approach, which makes it an appropriate choice for modeling technology adoption behaviors. Besides, PLS-SEM works effectively with small sample data sizes, even under the conditions of non-normality [130], which makes it an apt choice for the current study. Therefore, PLS-SEM was considered suitable for this study and was used in accordance with the guidelines given by Hair et al. [131].

4.2.1. Measurement model

The primary step in evaluating the PLS-SEM result involves examining the measurement model to assess the validity and reliability of the instrument. As all the constructs were operationalized using reflective indicators, corresponding guidelines by Hair et al. [131] were followed

Table 3
Demographic characteristics ($n = 183$).

Variable	Category	Frequency	Percentage
Gender	Female	66	36.07
	Male	117	63.93
Age (in years)	Less than 30	96	52.46
	31–40	55	30.05
	41–50	18	9.84
	51–60	7	3.83
	More than 60	7	3.83
Work Experience (in years)	0–5	117	63.93
	5–10	30	16.39
	10–15	12	6.56
	15–20	9	4.92
	20–25	5	2.73
	25–30	4	2.19
	30–35	4	2.19
	More than 35	2	1.09
Type of professional title	Resident Radiologist	106	57.92
	Consultant Radiologist	64	34.97
	Assistant Professor of Radiology	5	2.73
	Head of the Department of Radiology and Imaging	5	2.73
	Observer ship in Radiology	1	0.55
	Professor of Radiology	1	0.55
	Senior Registrar (Radiologist)	1	0.55

Source: Primary survey.

in the assessment.

As shown in Table 4, all constructs were tested to ensure an adequate level of scale reliability using indicator loadings and composite reliability (CR). Items with indicator loadings greater than 0.708 are accepted as it indicates that the construct explains more than 50% of the indicator's variance, thus meeting the acceptable item reliability [131]. Indicators, namely, LR_4, SI_4, and performance risk (PR_5) with indicator loadings (0.652, 0.614, and 0.673 respectively) less than the cutoff value, were removed from the further analysis as recommended by [130, 131]. The internal consistency reliability of the instrument was assessed by examining the CR. Statistical findings in this regard indicated that all the CR values were above the cutoff point of 0.7, satisfying the criteria [131]. Thus, the construct reliability of the instrument is established.

Following this, both convergent and discriminant validities were assessed to establish construct validity. Convergent validity was evaluated using the metric average variance extracted (AVE) [130]. From Table 4, it is evident that the constructs had AVE that are greater than the recommended threshold limit of 0.50 [130], which implies an adequate convergent validity. We followed the Fornell–Larcker criterion [132] recommended by Hair et al. [130] to assess the discriminant validity of the constructs. In accordance with the recommendation, all latent constructs had the squared root of AVE greater than their inter-correlation estimates with other corresponding constructs (Table 5) [130], implying adequate discriminant validity.

4.2.2. *Common method bias*

Common method bias (CMB) could be a concern in studies involving cross-sectional surveys [133]. Following Podsakoff et al. [133], we had employed a few ex-ante procedures to reduce method bias. First, the questionnaire was designed to be anonymous, giving the respondents enough room to express true perceptions. Second, while designing the questionnaire, we separated the independent and the dependent variables such that they did not appear in linear sequence [133]. Third, the measurement items were checked by a panel consisting of doctors and a PhD in the IS area for ambiguous terms, errors, and other inconsistencies to reduce method bias [133].

We also performed post hoc analysis to assess the degree of common method variance (CMV) present in our data [134]. Firstly, we performed Harman's single-factor test [135] to test for CMB. The largest factor that emerged accounted for 35.69% of the variance, which is less than 50%, the threshold recommended by Podsakoff et al. [133], indicating that CMB was not substantial.

Secondly, following the PLS approach of Liang et al. [136] and Wells et al. [137], we included an unmeasured latent method construct (ULMC) in the model to assess CMB [138]. The results are shown in Appendix D. The findings reveal that the average substantively explained variance of the indicators is 69.53%, while the average method-based variance is 0.71%. Thus, the variance of each indicator explained by its substantive construct is much greater than that explained by the common method factor (ULMC). Only four out of 40 paths from the method factor to the single-item constructs (measurement items) were significant. Also, the loading of these four significant paths were considerably smaller than the corresponding loading to the related latent construct. In the light of the obtained evidence, we concluded that CMV is negligible for this research.

Table 4
Reliability and validity statistics.

Latent Variable	Mean	Std. Dev	Item	Loading	CR	AVE
Behavioral intention (BI) to use	3.088	1.038	BI1	0.894	0.917	0.786
			BI2	0.887		
			BI3	0.878		
Disposition to trust technology (DT)	2.680	0.983	DT1	0.865	0.899	0.747
			DT2	0.872		
			DT3	0.856		
Effort expectancy (EE)	3.213	0.820	EE1	0.835	0.878	0.706
			EE2	0.816		
			EE3	0.868		
Inertia (IN)	2.740	1.019	IN1	0.839	0.899	0.748
			IN2	0.904		
			IN3	0.851		
Medico-legal risk (LR)	3.763	0.736	LR1	0.889	0.859	0.672
			LR2	0.842		
			LR3	0.719		
Performance expectancy (PE)	3.399	0.847	PE1	0.842	0.911	0.673
			PE2	0.791		
			PE3	0.848		
			PE4	0.77		
			PE5	0.848		
Performance risk (PR)	3.624	0.727	PR1	0.737	0.871	0.628
			PR2	0.767		
			PR3	0.838		
			PR4	0.824		
Perceived threat (PT)	3.362	0.858	PT1	0.765	0.889	0.616
			PT2	0.796		
			PT3	0.789		
			PT4	0.739		
			PT5	0.831		
Resistance to change (RC)	3.235	0.919	RC1	0.839	0.885	0.720
			RC2	0.864		
			RC3	0.844		
Social influence (SI)	2.795	0.806	SI1	0.889	0.872	0.695
			SI2	0.872		
			SI3	0.731		
Initial Trust (in Technology; TR)	2.797	0.840	TR1	0.803	0.912	0.675
			TR2	0.846		
			TR3	0.769		
			TR4	0.828		
			TR5	0.859		

4.2.3. *Structural model*

Following the standard assessment criteria [131], the overall explanatory power of the structural model was assessed using R^2, Q^2, and path coefficient β-values. We first evaluated the structural model for multicollinearity issues by examining the variance inflation factor (VIF). Multicollinearity refers to a condition where the measured variables are very closely related. It can distort the results of an SEM analysis [139]. The VIF values of all the constructs were found to be < 5, i.e., within the acceptable limits, which suggests that constructs in this model do not suffer from multicollinearity issues [131,139]. The VIF values are shown in Table 6.

The predictive validity (in-sample model fit) of the model was tested by estimating the R^2 values of the endogenous constructs. The R^2 values reported in Table 7 substantiate the model's predictive validity [140]. The predictive relevance of the model was examined using Stone–Giesser's Q^2 value using the blindfolding procedure [130]. All the Q^2 values (refer to Table 7) were found to be well above zero implying that the model had a high degree of predictive relevance for the endogenous constructs [130].

We performed PLSpredict cross-validation procedure with ten folds and ten repetitions [131,141] to gauge the model's out of sample predictive power. As all the indicators yielded $Q^2_{predict}$ values above zero (Table 8), we conclude that all the endogenous constructs outperformed the most naïve benchmark (indicator means from the training sample) [141]. As the prediction error distribution of the main indicators was not highly asymmetric, we based our assessment on the root mean square error (RMSE); however, the mean absolute error (MAE) does not lead to different findings in this case. Comparing the RMSE values with the naive linear regression model (LM) benchmark (Table 8), it is clear that the PLS-SEM model produces lower prediction errors for all the indicators. Therefore, we conclude that the model has high predictive power [131,141].

PLS bootstrapping procedure with 5,000 subsamples [130] was run to find the statistical significance and relevance of the path coefficients in the structural model. Table 9 summarizes the results of bootstrapping, i.e., path coefficient (β), t statistic, and significance value (p) of the paths in the proposed model. Fig. 2 illustrates the empirical results.

Table 5
Discriminant validity.

	BI	DT	EE	IN	LR	PE	PR	PT	RC	SI	TR
BI	***0.886***										
DT	0.476	***0.864***									
EE	0.554	0.183	***0.840***								
IN	–0.577	–0.216	–0.419	***0.865***							
LR	–0.458	–0.203	–0.395	0.451	***0.820***						
PE	0.740	0.406	0.578	–0.523	–0.332	***0.820***					
PR	–0.595	–0.321	–0.445	0.425	0.456	–0.591	***0.793***				
PT	–0.545	–0.315	–0.452	0.507	0.412	–0.432	0.337	***0.785***			
RC	–0.722	–0.356	–0.502	0.712	0.532	–0.560	0.507	0.590	***0.849***		
SI	0.647	0.334	0.472	–0.400	–0.333	0.663	–0.444	–0.459	–0.425	***0.834***	
TR	0.763	0.449	0.579	–0.500	–0.447	0.786	–0.586	–0.428	–0.615	0.653	***0.822***

Notes: As per the Fornell–Larcker [132] criterion, the diagonal values must be higher than any other value in the relevant row.

Table 6
Collinearity statistics.

Constructs	BI	RC	TR
DT			1.217
EE	1.750		1.545
IN	2.192	1.566	
LR	1.614	1.465	
PE	3.444		2.300
PR	1.807	1.377	
PT	1.767	1.438	
RC	2.961		
SI	2.084		1.845
TR	3.441		

Table 7
Predictive validity and predictive relevance.

Construct	R^2	Adjusted R^2	Q^2
BI	0.743	0.730	0.567
RC	0.629	0.621	0.442
TR	0.684	0.677	0.452

Notes: Assessing R^2 and Adjusted R^2; 0.75 = substantial, 0.50 = moderate, 0.25 = weak; Assessing Q^2; $Q^2 > 0$ = small, $Q^2 > 0.25$ = medium, $Q^2 > 0.5$ =large.

Table 8
PLSpredict assessment of manifest variables.

	PLS-SEM			LM		(PLS-SEM)–(LM)	
Items	RMSE	MAE	Q^2 predict	RMSE	MAE	RMSE	MAE
BI1	0.794	0.651	0.525	0.845	0.686	–0.051	–0.035
BI3	0.841	0.686	0.505	0.860	0.694	–0.019	–0.008
BI2	0.829	0.673	0.515	0.888	0.715	–0.059	–0.042
RC2	0.783	0.634	0.480	0.859	0.692	–0.076	–0.058
RC1	0.874	0.709	0.393	0.894	0.715	–0.020	–0.006
RC3	0.804	0.633	0.429	0.888	0.698	–0.084	–0.065
TR4	0.753	0.593	0.472	0.808	0.633	–0.055	–0.040
TR3	0.831	0.675	0.342	0.869	0.677	–0.038	–0.002
TR1	0.804	0.656	0.419	0.917	0.746	–0.113	–0.090
TR2	0.681	0.558	0.531	0.748	0.587	–0.067	–0.029
TR5	0.747	0.625	0.469	0.827	0.677	–0.080	–0.052

Notes: RMSE, Root Mean Square Error; MAE, Mean Absolute Error; LM, Linear Regression Model

First, we examined the impact of control variables on the BI. The results indicated that effects of the control variables on BI, i.e., Gender (β = 0.072, t=1.766), Age (β = 0.079, t=1.132) and Work Exp. (β = 0.058, t=1.060) were not significant at $p < 0.05$. Hence the impact of the control variables on BI was found to be insignificant. Furthermore, the inclusion of the control variables in the model did not improve the values of R^2 adj. (0.2% change), R^2 (0.9% change), or Q^2 (–0.5% change) significantly. Hence, they were excluded from further analysis.

Supporting results were observed for all the proposed hypotheses at

Table 9
Hypothesis testing.

Hypothesis	Path	*Β*	t-statistics	p-value	Significant?
H1a	PE → BI	0.188	2.735	0.006	Yes**
H1b	PE → TR	0.499	6.988	0.000	Yes***
H2a	EE → BI	0.004	0.086	0.932	No
H2b	EE → TR	0.173	3.228	0.001	Yes**
H3a	SI → BI	0.164	2.735	0.006	Yes**
H3b	SI → TR	0.190	3.018	0.003	Yes**
H4	DT → TR	0.151	3.100	0.002	Yes**
H5	TR → BI	0.228	3.196	0.001	Yes**
H6	RC → BI	–0.320	5.163	0.000	Yes***
H7a	PR → RC	0.164	3.072	0.002	Yes**
H7b	PR → BI	–0.091	1.612	0.107	No
H8a	LR → RC	0.154	2.712	0.007	Yes**
H8b	LR → BI	0.002	0.032	0.974	No
H9a	PT → RC	0.243	3.899	0.000	Yes***
H9b	PT → BI	–0.073	1.562	0.118	No
H10a	IN → RC	0.450	6.815	0.000	Yes***
H10b	IN → BI	0.005	0.092	0.927	No

Notes: β denotes the path coefficient; t denotes two-tailed t-test values; p-value stands for the significance level; Path significances: ****p* < .001; ***p* < .01; **p* < .05.

$p < 0.01$ except for the hypotheses H_{2a}, H_{7b}, H_{8b}, H_{9b}, and H_{10b}. Interestingly, when the direct effect was analyzed, RC (β = –0.320, $p < 0.01$), turned out to be the most prominent predictor of the BI ICDDSS. Among the positive predictors, in the order of their empirical relevance, TR (β = 0.228, $p < 0.01$), PE (β = 0.188, $p < 0.01$), and SI (β = 0.164, $p < 0.01$) had a significant positive impact on the BI to use. Thus, hypotheses H_{1a}, H_{3a}, and H_5 were supported. However, the relationship between EE and BI (H_{2a}) was not empirically supported. Similarly, the direct impact of the constructs PR (H_{7b}), LR (H_{8b}), PT (H_{9b}), and IN (H_{10b}) on BI were not supported. In brief, the significant predictors PE, SI, TR, and RC jointly explain roughly 73% (adjusted R^2 = 0.73; R^2=0.743) of the variance in the BI to use.

Additionally, PE (β = 0.499, $p < 0.01$), EE (β = 0.173, $p < 0.01$), SI (β = 0.190, $p < 0.01$), and DT (β = 0.151, $p < 0.01$) had significant positive influence on the initial trust and thus supporting the hypotheses H_{1b}, H_{2b}, H_{3b}, and H_4. The factors jointly explain about 67.7% (adjusted R^2 = 0.677, R^2 =0.684) of the variance in the initial trust.

Among the antecedents of resistance to change, IN (β = 0.450, $p < 0.01$), PT (β = 0.243, $p < 0.01$), PR (β = 0.164, $p < 0.01$), and LR (β = 0.154, $p < 0.01$) had significant positive influence on RC supporting the hypotheses H_{7a}, H_{8a}, $H_{9a,}$ and H_{10a}. Together, they were able to explain about 62.1% of the variance (adjusted R^2 = 0.621, R^2 =0.629) in RC.

4.2.4. *Mediation analysis*

A mediation analysis was performed to assess the effects of the mediating variables initial trust and resistance to change on their corresponding relationships in the proposed model. We followed the PLS-SEM mediator analysis using the bootstrapping method [142] to assess

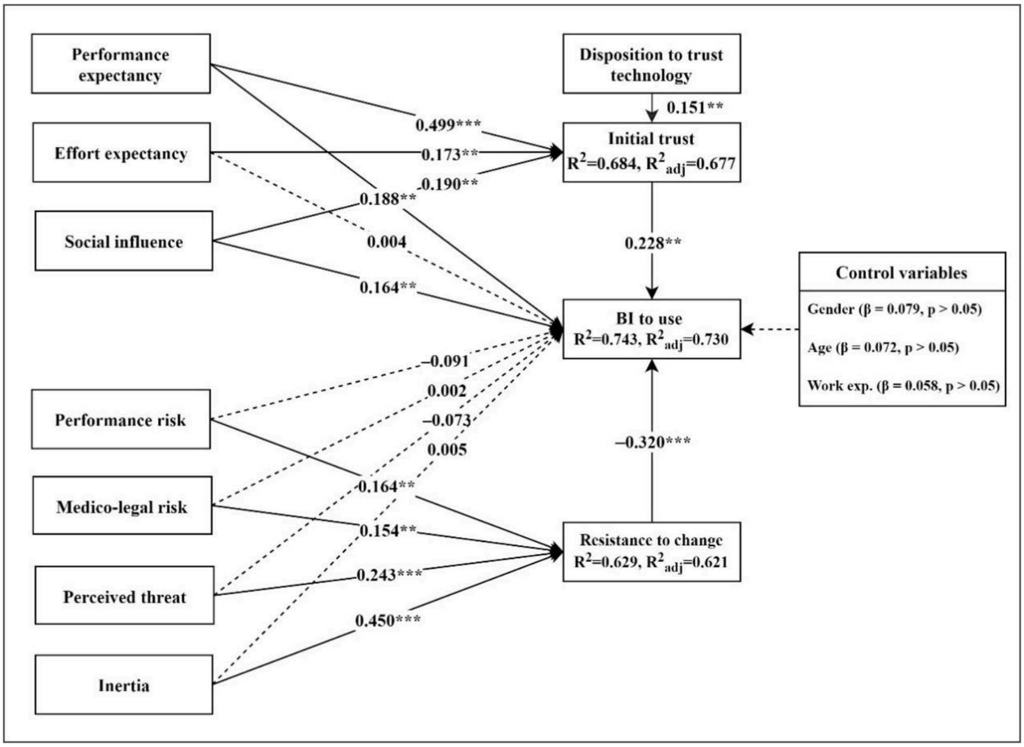

Fig. 2. Results of the Structural Model Notes: Continuous line indicates empirically significant relationship and a dotted line indicates a statistically nonsignificant relationship; significance level: ****p < .001; **p < .01; *p < .05.*

the mediation effect. The significance of both indirect and direct effects and the sign of the product of direct and indirect effects were examined to determine whether the mediation is full, complementary, or competitive partial mediation. Additionally, variance accounted for (VAF) was estimated to determine the magnitude of partial mediation. As per the rule of thumb in case of partial mediation, if VAF is found less than 20%, there is nearly no mediation; if the VAF is larger than 20% and less than 80%, the case could be characterized as a typical partial mediation [130]. The results of the mediation analysis are given in Table 10.

With respect to the mediator initial trust, all the indirect effects were significant (see Table 10). Then, we assessed the significance of direct effects. It is observed that the direct effect between EE and BI was not significant; thus, initial trust fully mediates the relationship between EE and BI. Since both the direct and indirect effects were significant, initial trust partially mediates the relationship between PE and BI (VAF=37.74%), and between SI and BI (VAF= 20.77%).

Similarly, with respect to the mediation of resistance to change, all the indirect effects were significant and direct effects were not significant. Thus, RC fully mediates the influence of PR, LR, PT, and IN on BI.

4.2.5. Importance–performance map analysis

An importance–performance map analysis (IPMA) [143] is a practical analysis tool to extend the interpretation of the traditional PLS-SEM analysis. For a specific target construct, the IPMA compares the structural model total effects (importance) against the average values of the latent variable scores (performance) to identify and prioritize the significant areas of improvement that can be subsequently addressed through managerial interventions [143]. The results of the IPMA analysis are presented in Table 11. Indicators of factors that are negatively related to the target variable BI were rescaled to facilitate comparison [143]. The scatter-plot diagram (Fig. 3) depicts the relative importance (x-axis) and performance (y-axis) of the direct and indirect determinant factors on the target construct BI. Two perpendicular lines passing through the mean importance and mean performance values divide the diagram into four quadrants.

Subsequently, the direct and indirect determinants of BI were divided into four categories according to their importance and performance scores. Quadrant I represent determinants of BI that are evaluated highly in both importance and performance parameters. PE is the only determinant that lies in this quadrant. Quadrant II contains

Table 10
Mediation analysis.

Relationship	IE	T	p	DE	t	p	Mediation type	VAF
Mediation of TR								
PE → BI	0.114	2.648	0.008	0.188	2.735	0.006	CPM	37.74%
EE → BI	0.039	2.278	0.023	0.004	0.086	0.932	FM	NA
SI → BI	0.043	2.398	0.017	0.164	2.735	0.006	CPM	20.77%
Mediation of RC								
PR → BI	–0.053	2.688	0.007	–0.091	1.612	0.107	FM	NA
LR → BI	–0.049	2.210	0.027	0.002	0.032	0.974	FM	NA
PT → BI	–0.078	3.109	0.002	–0.073	1.562	0.118	FM	NA
IN → BI	–0.144	4.217	0.000	0.005	0.092	0.927	FM	NA

Notes: IE, Indirect Effect; DE, Direct Effect; t, denotes for two-tailed t-test values; p stands for significance level; VAF, Variance Accounted For; FM, Full Mediation; CPM, Complementary Partial Mediation; NA, Not Applicable; [VAF>80%: Full mediation] [20% ≤ VAF < 80%: Partial mediation] [VAF< 20% : No mediation].

Table 11
Importance–performance map analysis.

Construct	Importance	Performance
DT	0.036	42.007
EE	0.055	55.313
IN (r)	0.141	56.493
LR (r)	0.067	30.925
PE	0.370	59.987
PR (r)	0.206	34.404
PT(r)	0.183	40.950
RC (r)	0.362	44.130
SI	0.267	44.869
TR	0.281	44.937
Mean	0.197	45.402

Note: (r), Rescaled to facilitate comparison.

determinants of BI showing above-average importance and below-average performance. Factors SI, TR, PR, and RC are the ones that lie in this quadrant. Quadrant III encompasses determinants of BI that have below-average values in both performance and importance parameters. It is observed that constructs DT, PT, and LR lie in this quadrant. Finally, constructs EE and IN were found to have above-average performance, but below-average importance hence lie in Quadrant IV.

5. Discussion

This research investigated the determinants of medical practitioner's intention to use ICDDSS in clinical practice. This section discusses the research findings and the inferences emerging from this study. Among the enablers considered in this study, PE, SI, and TR emerged as significant predictors of medical practitioner's usage intentions. In particular, TR ($\beta = 0.228$) had comparatively greater effect on the intention to use than PE ($\beta = 0.188$) and SI ($\beta = 0.164$). This corroborates the evidence found in our qualitative study, where trust was reported as a precursor to usage intentions. This finding is also in line with the prior studies, which argued for the inclusion of "trust in technology" as an antecedent of CDSS adoption [35,36,67]. The result implies that practitioners who believe that ICDDSS will be able to provide reliable, dependable, accurate, and safe diagnostic assistance are more likely to develop a positive intention towards using the system. Similarly, practitioners who perceive ICDDSS to be useful in ways that would help them make a quicker, more accurate diagnosis, increase productivity, and reduce workload (PE) are more likely to have a positive intention to adopt ICDDSS. Additionally, results also suggest that medical practitioners who believe that their colleagues, top management, and professional bodies (medical associations) support the use of ICDDSS in clinical practice are more likely to have a positive intention to adopt ICDDSS.

Interestingly, EE has unexpectedly emerged as an insignificant predictor of ICDDSS usage intention, rejecting the hypothesis H_{2a}. Although this is contrary to propositions in the original UTAUT [70], it corroborates the assertions of Lee et al. [144] and Sun and Zhang [145] that ease of use is an inconsistent determinant of use. A recent study on the healthcare professional's acceptance of care robots also reported a similar finding [146]. The reason for this could be that radiologists are used to highly complex machines in their routine clinical practice, and the ease of use associated with the system may not factor in as an influential criterion in the adoption-related decision-making. Another reason may perhaps be that radiologists did not foresee any difficulty in using ICDDSS, and they perceived the use of ICDDSS to be as easy as using their current systems/machines.

Our research confirms that medical practitioner's resistance to change was driven by inertia ($\beta = 0.450$), perceived threat ($\beta = 0.243$), performance risk ($\beta = 0.164$), and medico-legal risk ($\beta = 0.154$) in the order of the relative magnitude of their influence. This means that the practitioner's proclivity to continue with old ways/methods, even if there are better alternatives (inertia), is the major contributor to the resistance. Previous studies [26,29,99] have reported a similar tendency in the IS adoption. Furthermore, the radiologist's fear of being substituted/outdated in the long run either by machine or non-specialists empowered with AI technology and the adverse consequence

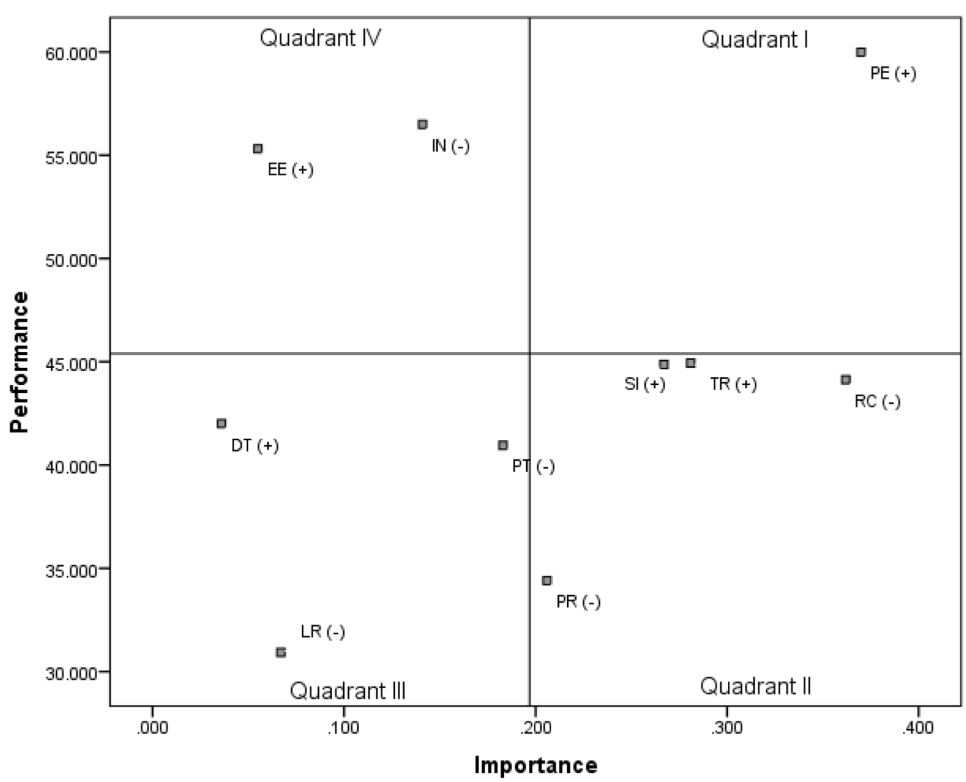

Fig. 3. Importance–Performance Map (construct level) on the target construct BI.

following adoption like reduced pay, loss of control, deskilling, dependency (PT) significantly contributes to the resistance. Our qualitative study supports our findings, and comparable results have been reported by Sambasivan et al. [67], where "perceived threat to professional autonomy" was identified as an inhibitor of CDSS adoption. Performance risk and medico-legal risk were also found to be significant predictors implying that medical practitioner's concerns about uncertainty prevail over the performance of ICDDSS, and the legal consequences of following the error-prone advice of intelligent systems will add to his/her resistance. These results validate the apprehension about medico-legal risk reported in our qualitative study (see Appendix B). Arguments by the opinion papers on AI applications in healthcare [124, 147] are also in line with these findings.

Furthermore, the quantitative study indicates that the initial trust in the ICDDSS relies on four factors, namely PE, EE, SI, and DT. Among the predictors of initial trust, PE ($\beta = 0.499$) is found to have the largest impact followed by SI ($\beta = 0.190$), EE ($\beta = 0.173$) and DT ($\beta = 0.151$). Results are consistent with the literature on IS adoption and trust [22, 93]. This means that in the case of ICDDSS, the practitioner's perception of the functionality and usefulness of the product (PE) contributes the largest to the initial trust formation. Similarly, in the absence of prior direct experiences with the ICDDSS, the opinion of colleagues, seniors, and leadership of professional bodies/hospital (SI) will play a vital role in shaping the initial trust perceptions. Going by the same logic in the absence of direct experiences, the user's disposition/propensity to trust technology, in general, will determine the amount of trust in the target technology [94]. Additionally, although EE, "the degree of ease associated with technology," was found to have no significant direct effect on the intention to use, it is found to influence trust formation.

Results of mediation analysis revealed that initial trust fully mediates the relationship between EE and BI and partially mediates the effect of PE and SI on BI. The mediating variable describes "how" the independent variable will predict the dependent variable [148]. In this case, the entire causal relationship between EE and BI is channeled through Initial trust, i.e., EE leads to the formation of initial trust perceptions, and the level of initial trust determines the intentions to use. While in the case of PE and SI to BI relationships, the mediator initial trust is responsible for only a part of the relationship between the independent variables PE and SI and the dependent variable BI. Together the finding implies that the factors PE, EE, and SI are necessary, but not sufficient conditions to ensure usage intentions. The practitioners who have positive perceptions on factors, PE, EE, and SI, might still not intent to use if his/her trust is undermined by other factors such as disposition to trust. These findings are in line with an earlier study by Fan et al. [22]. Similarly, resistance to change is found to fully mediate the influence of PR, LR, PT, and IN on BI. This implies that performance risk, medico-legal risk, perceived threat, and inertia determines the medical practitioner's resistance to change, and resistance to change eventually determines their intention to use ICDDSS. The full mediation also underlines that the factors PR, LR, PT, and IN are indeed the predictors of "resistance to change," and any effect on the main dependent variable BI is indirectly channeled through the intermediate variable resistance to change.

The IPMA results lead us to meaningful insights on the significant improvement areas that can be addressed through managerial interventions. The constructs lying in quadrant II having higher than average importance and lower than average performance are of the highest interest to achieve improvement in the target construct BI. Managerial activities should, thus, prioritize improving the performance of constructs TR, SI, PR, and RC to bring about improvement in BI to use ICDDSS. Factors in quadrant I are generally emphasized as competitive factors essential for gaining and sustaining the target construct values at a high level. Hence factor PE's performance should be maintained to sustain the BI to use ICDDSS at high levels. Since both importance and performance is low for quadrant III, it is not sensible to focus further improvement effort on these factors (LR, PT, and DT) as long as the magnitude of their influence on the target variable does not change. Factors in quadrant IV are generally regarded as having excess performance in comparison with its relative importance to the target construct. To avoid a possible overkill, managerial efforts should focus on other areas than the attributes in this quadrant. Additionally, even though PT is in quadrant III, PT has an importance value (0.183) very close to the mean importance (0.197), indicating that it is comparatively an important construct. Hence, we suggest that PT should be treated like variables in quadrant II.

Finally, measurement items, namely, SI_4, LR_4, and PR_5 (see Appendix C), were excluded from the analysis due to lower than cutoff loadings (<0.708). The item SI_4 checked if medical practitioners believed that many doctors across the globe used ICDDSS in their practice. While the item LR_4 measured if medical practitioners believed that ICDDSS manufacturers were trying to shield themselves from the legal liability using product disclaimers. The final item dropped was PR_5, which measured if practitioners believed that ICDDSS were technically mature so far. Even though these items had content validity (checked by a panel), these three items were dropped on technical grounds with a relatively low loading difference from the cutoff. Future research can check if these items can measure their corresponding constructs adequately.

5.1. Implications to practice

The results of this study offer actionable insights to ICDDSS marketers, system implementers/healthcare IT managers, ICDDSS developers/vendors, and policymakers on possible measures to enhance the adoption and alleviate medical practitioner's resistance to ICDDSS adoption. Firstly, PE was found to be a significant predictor of adoption intentions; the ICDDSS marketers must focus on communications that highlight the benefits of using ICDDSS (speed, accuracy, productivity improvements, and workload alleviation), which are appealing to the medical practitioners. In addition, the marketers can also offer demonstration/training programs using real cases to counter the unrealistic expectations that medical practitioners might have about the capability of AI systems. Experiencing the benefits of ICDDSS firsthand in the daily task will improve the PE and foster user acceptance.

Similarly, a significant relationship between SI and BI implies that in order to ensure faster diffusion of ICDDSS, marketers should devote more resources to establish relationships with national/regional medical professional bodies, hospitals, and senior leadership in the radiologist community. For example, organizing hands-on training programs for practitioners on ICDDSS and live interactions with medical practitioners who are involved in ICDDSS research and development, in collaboration with professional bodies will help improve adoption. Furthermore, the significant relationship between initial trust and adoption intentions implies that marketers should be able to demonstrate the reliability, dependability, accuracy, and safety of their devices in clinical practice through scientific evidence (e.g., certifications from regulatory bodies like FDA, scientific reports on clinical trials, etc.) to build trust in the system. In summary, marketing resources should be devoted to trust-building and relationship building efforts with professional medical associations to enhance adoption.

In addition, our research provides important indications as to why medical practitioners would resist adopting ICDDSS. This has important implications for system implementers/healthcare IT managers and ICDDSS developers/vendors. In this context, the perceived threat was found to contribute to user resistance significantly. Taking a cue from this empirical finding, we suggest that system implementors/ healthcare IT managers should recognize and quantify such threats by openly communicating with medical practitioners using focus group discussions or anonymous surveys during various stages of adoption. Also, the system implementers should try to take radiologists into confidence by providing assurance against any layoffs, reduction in income, or loss of professional autonomy before the implementation. Furthermore, inertia is found to be the strongest determinant of resistance in our study. It implies the system implementors/healthcare IT managers should identify the primary sources of inertia, i.e., switching costs, habitual use, or sunk cost [99], and take adequate measures to encourage habit disruption and reformation, change user perception of the costs associated with switching to new systems to alleviate inertia. In short, they should employ strategies to curtail resistance by identifying and prioritizing the critical sources of inertia.

Additionally, a significant relationship between perceived threat and resistance to change implies that the ICDDSS developers/vendors should ensure that the nature of the system and processes are designed in a way that is less threatening (augmenting the radiologist rather than trying to reduce his/her role in clinical decision-making). System implementors should ensure that users of the system can still act independently and overrule the decisions made by ICDDSS if deemed necessary. A significant positive effect of performance risk on resistance to change implies that system developers should work towards easing the practitioner's performance-related concerns by demonstrating the reliability, accuracy, and capability of the devices (e.g., certifications and approvals from regulatory agencies). Finally, the perception of medico-legal risk is found to contribute to user resistance significantly. Interpreting this with the fact that present legal doctrines are insufficient to address AI-related medical malpractice [124], policymakers need to craft new legal standards and models that are fair and predictable for AI-related medical malpractice. Doing so will help reduce the risk perceived by medical practitioners and promote the use of AI-based decision aids in medical diagnosis.

Thus, our research presents a comprehensive understanding of the determinants of medical practitioner's intention to use ICDDSS. These insights will aid system implementers/healthcare IT managers and developers to better understand why medical practitioners would resist the use of ICDDSS in order to formulate pragmatic strategies for evaluating systems, explain how medical practitioners would respond to them, and improve adoption by altering the nature of the systems and procedures by which they are deployed. It could also persuade policymakers to craft new legal standards that can assuage medico-legal risk associated with ICDDSS adoption. We hope insights from our study will help facilitate the design and deployment of ICDDSS that are purposeful and acceptable to their target users.

5.2. Theoretical contributions

The study contributes to the literature in several ways. First, this is one of the pioneering studies on the adoption of AI technology for medical diagnosis, which is projected to have wide prospects in the future of healthcare delivery [3]. While there have been extensive studies focusing on medical practitioners' adoption of various HITs, very few have focused on clinical decision-making applications of AI [19]. Further, the unique characteristics of ICDDSS such as autonomous decision-making, self-learning ability, accuracy levels exceeding human experts, and non-transparent nature of the algorithms present a range of new concerns and challenges, such as the threat of loss of autonomy, fear of replacement, dependency, concerns about patient safety, and legal liability of misdiagnosis [18,22-24]. These contextual issues make it difficult for the prior technology adoption models on HIT to explain the ICDDSS adoption. Thus, this study extends the IS adoption literature [69,70,90] by introducing a new adoption object (ICDDSS) and subject (radiologists) in the context of a developing country.

Second, we theoretically integrated the notion of user resistance to a unified model of IT usage in a healthcare IT adoption setting. Given that the existing IT usage theories provide only a partial explanation of IT usage intention, additional factors are required to explain how the user assesses the overall change introduced by the novel technology [69,90]. This is particularly relevant for AI-based technology as no prior studies with the exception of [166], have focused on the resistance aspect, even though user resistance is apparent in various AI technology adoption settings like autonomous vehicles, medical AI, etc. [24]. The prior study [30], a case study on the failure of a healthcare AI project implementation, identified user resistance as a key reason for project failure and emphasized the need to anticipate user resistance during AI technology implementation. We demonstrated that the prediction of ICDDSS use intention could be greatly improved by simultaneously considering the role of enabling (PE, EE, etc.) and inhibiting (resistance to change) perceptions in the formation of IT usage intentions. The current study thus offers theoretical insights for researchers into what could motivate or inhibit users from using ICDDSS technology.

Third, we contribute to the user resistance literature, specifically, the stream of literature which conceptualized "user resistance" as a perception that precludes potential behavior, defined as a "generalized opposition to change caused by the anticipated adverse consequences of IS induced change"—resistance to change [28]. Bhattacherjee and Hikmet's model of perceptual resistance to change [28] explains user resistance through a perceived threat lens. Despite the importance, very little is known about the antecedents of user resistance [28,77]. We extend the Bhattacherjee and Hikmet's model [28] in the context of ICDDSS adoption by revealing the additional antecedents of resistance to change namely, performance risk, medico-legal risk, and inertia. Furthermore, our study validates the mediating role of resistance to change in the IS adoption-related decision-making. Our study demonstrated that the pre-adoption perceptions of performance risk, medico-legal risk, perceived threat, and inertia form the basis for the development of resistance to change, which eventually determines the intention to use. This is one of the very few studies that validated the mediating role of resistance to change in the technology adoption setting in the literature [27,28] and is also the first to do so in the AI technology adoption setting.

Additionally, our study also contributes by operationalizing and testing an instrument for measuring the novel construct "medico-legal risk" in the context. Although opinion papers [96,124] have reported medico-legal liability as a key concern related to medical AI adoption, our study is the first to provide empirical evidence about the impact of this inhibiting perception on the ICDDSS adoption decision-making. Further, the study also highlights the differences in the relative impact of the predictors of resistance to change. The novel association between medico-legal risk and resistance to change reported by this study though smaller than the other predictors of resistance to change (inertia, perceived threat, and performance risk), is positive and statistically significant. Further, the study extends the understanding of perceived threat [28] by enriching the conceptualization and operationalization of the construct in this context through a qualitative study. Accordingly, perceived threat in the context of ICDDSS adoption can arise from the threat of replacement (by ICDDSS directly or by technicians or doctors (non-specialists) assisted by ICDDSS), the threat of unemployment, and the threat of skill deterioration and dependency.

Fourth, our findings strengthen the case for the pivotal role of "trust in technology" in technology adoption models. Thus, in addition to being a critical factor for ICDDSS usage intention, we observe that initial trust (in technology) remains a crucial mediator in the adoption decision-making. We thus extend the prior research [35,36] by demonstrating the mediating role of initial trust in technology in the ICDDSS adoption decision. Medical practitioners' pre-adoption evaluation of ICDDSS technology provides a basis for the formation of initial trust in the ICDDSS technology, and this level of trust eventually plays a crucial role in determining the intention to use. Considering the inadequate research on the role of mediators between the enabling factors and behavioral intentions in the technology adoption models (e.g., UTAUT) [22,118,119], the empirical evidence on the mediation of trust in technology provided by this study is a valuable addition to the literature on both trust in technology [91,94,111,114] and IS adoption [69,90]. Moreover, this research makes a clear distinction between various stages of trust, which is often overlooked in the previous research pertaining to the adoption of novel technologies [22,117].

Finally, our study advances the SQB theory [95] by extending it to the ICDDSS adoption context. In the IS literature, the SQB theory has been applied to explain IT adoption in different IS transition contexts, such as incumbent-new HIT [28], off- to online cloud-based system [26, 27], email to collaborative file sharing system [99], etc. To the best of our knowledge, SQB theory has received little attention in the health technology adoption context [26-28] and AI-based technology adoption context [32]. The existence of SQB will be a major barrier in the transition of medical practitioners from incumbent systems to ICDDSS [32]. This study contributes to the knowledge gap by confirming that SQB theory can be used to explain the medical practitioners' resistance to the change induced by the introduction of AI technology to clinical practice. Further, our study contributes to the SQB theory [95] by identifying risk factors (performance and medico-legal) and perceived threat to explain the rational decision-making viewpoint of SQB theory (preference to status quo due to psychological uncertainty) in the context of ICDDSS.

5.3. Limitations and future research directions

There are some limitations to the current study, some of which may offer opportunities for future research. The first one is pertaining to the sample chosen for the study. Although the qualitative part of this research made use of the perceptions of radiologists from an international discussion forum, the data collected for the quantitative part of the study was geographically limited to respondents (radiologists) from India. Thus, generalizing the findings to other contexts, especially developed countries, might be difficult. Further, we did not account for the impact of cultural factors on the adoption intention. Prior studies have emphasized the need to evaluate the role of cultural factors in IS usage behavior [149,150]. Therefore, replicating the findings in the context of different geographies (developed vs. developing countries) is considered necessary. Additionally, future research can adopt a cross-cultural perspective to understand the differences in the adoption behavior.

The second limitation is about the choice of target technology (ICDDSS for radiology) and target respondents (radiologists). We did not consider other examples of ICDDSS intended for GP or other subspecialties in medicine. It is likely that ICDDSS intended for GPs will not be perceived as a possible threat to their profession, unlike in the case of radiologists. Future studies can, therefore, evaluate the validity of this model in the context of the ICDDSS intended for GPs and specialists from other subspecialties of medicine.

Third, our research dealt with a pre-adoption stage and therefore did not measure the actual usage of ICDDSS; instead, it focused only on the medical practitioner's intention to use ICDDSS. Future research can test the adoption in an actual-use context and examine how the factors perform in that context. Researchers may also explore the dynamics between stated intentions and actual usage. Further, future studies can benefit from using actual objective data, such as time spent or the number of logins instead of perceptual/self-reported measures.

Last, as this research focused on the pre-adoption stage, it examined the role of initial trust in the adoption, but did not address the role of continuous trust [151], which is formed after the actual encounter/experience with the technology. Prior research in IS indicates that continuous trust plays a pivotal role in the continuance of technology use [151]. Therefore, we call for future research to examine the formation process of both initial and continuous trust in AI-based technologies in general and ICCDSS in particular.

6. Conclusion

The current study undertook a comprehensive investigation of factors influencing medical practitioners' intention to use ICDDSS using a mixed-methods approach. The study presents a model of ICDDSS adoption intention that integrates the theoretical paradigms of UTAUT, SQB, and trust in technology using the dual-factor model of IS usage. The empirical testing revealed that PE, EE, SI, and initial trust in technology are the key enablers, while resistance to change is the main inhibitor of the intention to use ICDDSS. Further, inertia, perceived threat, medico-legal risk, and performance risk collectively contribute to the medical practitioners' resistance to change and ultimately decrease their intention to use. The study contributes by providing a holistic perspective of critical factors (enabling and inhibiting) that influence the intention to use ICDDSS. The findings of this study can serve as a basis for understanding the medical practitioners' response to the overall change introduced by the novel AI-based ICDDSS in clinical practice. The study also presents practical measures that will aid the main stakeholders in managing the user resistance to change and enhancing the practitioners' adoption of ICDDSS technology. The study also outlines directions for future research on this topic.

CRediT authorship contribution statement

Ashish Viswanath Prakash: Conceptualization, Methodology, Investigation, Software, Formal analysis, Visualization, Writing – original draft. **Saini Das:** Methodology, Writing – original draft, Supervision, Validation, Writing – review & editing.

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.im.2021.103524.

APPENDIX A, Overview of interview data sources

Respondent Code	Gender	Age	Designation	Qualification	Work Experience	Place
R1	M	29	DNB Radiology Resident (Secondary)	MBBS, DNB (Pursuing)	1	Mumbai
R2	M	50	Senior Consultant Radiologist	MBBS, MD	18	Mumbai
R3	M	28	DNB Radiology Resident (Primary)	MBBS, DNB (Pursuing)	1	Mumbai
R4	F	35	Senior Consultant Radiologist	MBBS, DMRE	8	Mumbai
R5	M	34	DNB Radiology Resident (Secondary)	MBBS, DNB (Pursuing)	4	Mumbai
R6	M	30	Observer ship (post MD)	MBBS, MD	4	Mumbai
R7	M	28	DNB Radiology Resident (Primary)	MBBS, DNB (Pursuing)	1	Mumbai
R8	F	30	Consultant Radiologist	MBBS, MD	6	Mumbai

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Respondent Code	Gender	Age	Designation	Qualification	Work Experience	Place
R9	F	66	Consultant Radiologist	MBBS, MD	39	Mumbai
R10	M	62	Head of Department of Imaging	MD, DMRD, DMRE, FICR	29	Mumbai
R11	M	50	Senior consultant Radiologist	MBBS, MD	21	Mumbai
R12	M	35	Consultant Radiologist	MBBS, MD	4	Bangalore
R13	F	46	Consultant Radiologist	MBBS, DMRD, DNB	23	Mumbai
R14	F	55	Head of Department of Imaging	MBBS, MD	27	Delhi
R15	M	32	Consultant Radiologist	MBBS, DNB	3	Thanjavur

Note: DNB, Diplomate of National Board; DMRE, Post Graduate Diploma in Medical Radiology and Electrology; DMRD, Diploma in Medical Radio-Diagnosis; MD, Doctor of Medicine; MBBS, Bachelor of Medicine & Bachelor of Surgery.

APPENDIX B, Summary of thematic analysis

Theme	Sub Theme	Sample excerpts from qualitative study-1 (Netnography) (N=89)	Sample excerpts from qualitative study-2 Interview (N=15)
Perceived threat	Threat of being replaced by Doctors from other specialties	"*What about a neurologist reading his own CTs? What about a primary care doc dictating all his own chest radiographs and CT's with the assistance of an AI software?—that is going to be the threat. Losing imaging to the other docs who own the patients and are willing to read their own stuff. This turf war isn't going to be radiologist vs computer, it's going to be radiologist vs. every other -ologist, who equipped with AI, will feel confident interpreting their own imaging*" [N64]	
	Threat of being rendered redundant /obsolete	"*by the time I could get good at it both me and my knowledge could be rendered entirely and permanently obsolete by such an algorithm. I fear that we can easily become the switch board operators of medicine* […] *I've been experiencing a serious existential fear for a while now due to this*" [N6]	"*people like me trained in radiodiagnosis are worried if this could make our jobs redundant. I'm worried once the technology matures whatever we have learned over the years may become obsolete. We will surely lose our edge*" [R12]
	Threat of losing autonomy in job	"*My angle of attack as an evil admin would be—sell AI as a 'support tool', gain the required evidence for the bureaucrats and then through decreased demand make these pesky doctors with 7 years of postgraduate education belly dance for me. Dance, doctah, dance!* " [N7]	
	Threat of replacement (full/partial) by machines	"*You might have a very myopic definition of 'replacement' images are fed to the AI and the AI reports back to the referring physician, and no intervening human is required. However, if you have a more real-world definition of replacement AI will lead to needing half as many radiologists as we used to have then certainly it becomes more of a certainty that AI will replace A lot of rads*." [N89] "*What happens if someday radiology AI becomes good enough and reliable that […] policy makers allow report go out without a radiologist finalising/signing it.* " [N44]	"*Few residents here have even started asking whether we should take radiology branch or not because they think that their work can be replaced by machines.*" [R6]
	Threat of deskilling	"*I feel that 50 years from now, I may lament that my trainee cannot read a CT as well as me*" [N39]	
	Threat of decline in pay	"*if workload goes down by 50 percent, I'd assume pay will as well?*" [N76] "*I'd be more worried about the next surplus of rads with the corps becoming dominant, and salaries dropping to unsustainable levels*" [N23]	
Medico-legal risk	Legal liability of the doctor	"*If there's an AI miss or wrong interpretation, is the AI company going to take all liability? They still want a radiologist to overread/sue.* " [N75] "*Of course, the companies will not be liable. It will be the radiologist that will be liable for all of the findings.* […] *the radiologist will have to edit and approve the report, accepting ultimate liability*" [N44]	"when the machine goes wrong, the poor guy if h*e is trusting the system blindly or if he is an inexperienced beginner, the error would pass through. Who is going to bear the responsibility?* […] *the burden of liability will be upon the doctor who signs the report.* " [R12]
	Companies evade legal accountability	"*So, who do they sue if software fails, obviously the software dev company? Their end user license agreement will say 'the accuracy of diagnosis will depend on several factors etc. etc.' They are not going to stick out their neck for any misdiagnosis.* " [N32]	
	Risk of Malpractice Litigations	"*They don't even take into account the medical malpractice issues*" [N86] "*In the US, many have pointed out that one thing that humans add is someone to sue* […] *through the years I have learned that the attorneys are intent upon securing their incomes by insuring that there continue to be lawsuits. And their lobby is very powerful*" [N22]	"*Tomorrow if there is an issue and the patient sue you where are you going to stand? I am surprised that in the US they are working on it without addressing the medico-legal part.*" [R11]
Performance risk	Risk of malfunction/ failure	"*AI, even if it's a 99.99% approximation of a human imager, are prone to catastrophic errors with a wholly unacceptable failure mode, and that's what make it unacceptable for mission critical environment like aerospace or medicine.* " [N39]	
	Risk of false positives and false negatives	"*A lot of radio-logic exams have artefacts. I think the robot would malfunction when it sees the indication of PE vs chole vs appy vs renal stone*" [N12] "*I fear for a CAD-like scenario, where PACS-integrated 'little helpers' will bombard us with incidental findings with little clinical relevance*" [N6]	"*we can expect a lot of errors, it would trigger for everything that it is not supposed to.*" [R12] "*I think these are not very sensitive, larger things it may pick up but it would leave some things which are very minute like small fractures*" [R8]

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Theme	Sub Theme	Sample excerpts from qualitative study-1 (Netnography) (N=89)	Sample excerpts from qualitative study-2 Interview (N=15)
	Technology not mature enough for clinical use	"*AI has not developed enough yet for clinical duties. Nothing off the shelf now is ready for the stage*" [N44]	"*Firstly, in its current form AI cannot do anything great, it would easily take another 10-15 years to see some working prototype that is fit for clinical use*" [R2]
Performance expectancy	Increase efficiency and productivity	"*the tech will make us faster and more efficient. The commercial airline pilot comes to mind—the machine does the repetitious tasks (like calling negative head CT's negative) while we have more time to look at complex cases*" [N81] "*…aim should be to use AI to screen radiology images and confidently screen normal from abnormal. This single step can reduce a radiologist reporting workload by approximately 50–60%*" [N74] "*We'll become more efficient, and slowly need fewer radiologists. Probably in 30 years be employed computer jockeys troubleshooting 500 CTs a day.*" [N81]	"*if we have this technology which would allow us to filter normal scans from the abnormal, the time spend by the radiologists will be reduced*" [R13] "*It can increase the productivity by 40–50% something that you do across 8 hours can be now done in 4–5 hours*" *[R10]*
	Improve accuracy/reduce errors	"*…will be able to achieve better diagnostic accuracy by working with the AI*" [N39] "*AI will greatly assist by reducing missed findings*" [N61]	"*It will pick up the subtle things which we can miss in fast reporting*" [R6]
	Relieve from repetitive and tedious tasks	"*Human beings aren't great at going through a bunch of images and noticing every little abnormality, which is why you keep seeing articles showing miss rates on CTs of around 30%....the majority of our time and effort is not spent on 'higher level' thinking* […] *but rather making sure we don't miss incidental findings* […] *If the computer can take care of that part, and I can focus on high-level decision making, that's great.*" [N8]	"*It can help us in doing things which are boring and often time consuming to do like segmenting small structures, volumetry, etc.* […] *When AI comes in there helping us with these mundane tasks then it will be more of a kind of utility.*" [R8]
	Improve consistency in reporting	"*Will confidently prioritize these studies to the top of the reading list with the same confidence even if its 3AM*" [N6]	"*A human being may not always perform consistently you know because of various biases and cognitive limitations; a machine however will not have this problem*" [R2]
	Improve effectiveness		"*particularly for young radiologists who may not be confident about certain things, AI will boost the confidence for that particular diagnosis. Particularly when it is a case of emergency situation like during a night call*" [R5]
Trust (in ICDDSS technology)	Lack of trust in AI technology	"*I am willing to use it, but here are two problems. If I can't always trust the 'diagnostic decisions' rendered by AI, then I have to double check all of its work, making it useless for me*" [N1]	"*there will be some issues about the credibility of AI results so there will be a role of humans, lot of results will come up and there will be variations. It is just not that the machines says something and we are going to accept that*" [R13]
	Lack of trust in AI training methods	"*Many have already described the problem with the* 'gold standard' *or as they call it the* 'ground truth'. *Put succinctly, the* 'right answer' *was a single interpretation of the film by a radiologist, which may not even have accurately represented the radiologist's impression*" [N22] "*What if one of the radiologists who was marking and annotating "clinically relevant" lesions for the NIH study was a bit of a goofball? Now all his mistakes are being used as the template for AI and every splenule will be read as a possible metastatic lesion.*" [N62]	
	Lack of transparency and explainability	"*AI cannot explain how it comes to a conclusion. This is a problem when findings are subtle*" [N61] "*AI/black boxes are literally that. We don't know what goes on in the box*" [N20]	"*Will computer be able to answer our queries if we have doubts about its assessments and reports?*" [R2]
	Skepticism about the purpose of AI	"*it's initially marketed as an aid/second reader etc. the endgame being revealed only after use of such algorithms has become commonplace—that's my 'slippery slope' hypothesis*" [N6]	
	Skepticism about the claims	"*From long experience, I do not believe initial reports* […] *I have seen so many studies/therapies/computer techniques with great promise and great initial papers get tossed in the waste can after they were moved to actual clinical practice.*" [N22] "*we all need to be very sceptical about this data. Very sceptical. it has pointed out that more than 50% of the major results in the medical literature are wrong. These systems need to be tested extensively in real life situations by people who did not develop the systems*" [N22]	
	Need for more clinical evidence		"*I would like to see these systems backed by some good amount of clinical validation studies. There should be enough scientific evidence to believe that these systems would actually improve diagnostic accuracy or speed. That would instil more trust among the doctors*" [R12]
User resistance	Resistance to change	"*Radiologists respond to this with passive resistance or simple indifference and therefore are out of the decision loop. […] As a profession, we need to be very aggressive in controlling how this is brought into standard medical practice […] Remaining in a position of control will allow is to reject those technologies that are not useful, and be the leaders in those that are.* " [N22]	"*Our medical associations should lobby for protective measures that ensures that the final decision is taken by the doctor, not by some algorithm, in that way protecting our jobs*" [R12] "*machine doing reporting is not acceptable right now[…] I'm not keen on using it as of now*" [R8]

Note: N1-89, refers to identifying code given to individual participants of qualitative study 1 (Netnography); R1–15, refers to informant code given to respondents in qualitative study 2 (semi-structured interview).

APPENDIX C, Measurement items

Constructs	Code	Indicators	Source
Performance expectancy	PE1	Using AI-based ICDDSS would enable me to make diagnosis decisions more quickly.	Adapted from [70]
	PE2	Using AI-based ICDDSS would improve the accuracy of my diagnosis	
	PE3	Using AI-based ICDDSS would increase my productivity.	
	PE4	Using AI-based ICDDSS would help reduce my workload	
	PE5	Overall, I would find AI-based ICDDSS useful in my job	
Effort expectancy	EE1	I believe learning to use AI-based ICDDSS would be easy for me.	Adapted from [70]
	EE1	It would be easy for me to become skillful at using the AI-based ICDDSS.	
	EE3	Overall, I believe that AI-based ICDDSS would be easy to use.	
Social influence	SI1	I think my colleagues, whose opinion I value, support the use of AI-based ICDDSS in practice	Adapted from [22]
	SI2	I think the professional society that I'm part of (Medical Associations) supports the use of AI-based ICDDSS in practice	
	SI3	I think my organization's (Hospital) top management supports the use of AI-based ICDDSS in practice	
	SI4	I think many doctors across the globe are using AI-based ICDDSS in their practice*	
Initial trust (in technology)	TR1	I believe AI-based ICDDSS can provide reliable diagnostic assistance	Adapted from [22,152]
	TR2	I believe AI-based ICDDSSs are dependable for diagnosis assistance	
	TR3	I believe AI-based ICDDSS can provide highly accurate diagnostic assistance	
	TR4	I believe AI-based ICDDSS can provide safe diagnostic assistance	
	TR5	Overall, I believe I can trust AI-based ICDDSS for diagnosis assistance	
Disposition to trust technology	DT1	My typical approach is to trust new technologies until they prove to me that I shouldn't trust them.	Directly adapted from [94]
	DT2	I usually trust a technology until it gives me a reason not to trust it.	
	DT3	I generally give technology the benefit of the doubt when I first use it.	
Performance risk	PR1	I'm worried whether AI-based ICDDSS will really perform as well, as it is supposed to	Adapted from [153]
	PR2	The thought of using AI-based ICDDSS causes me to be concerned about how reliable its service will be	
	PR3	I am concerned that AI-based ICDDSS will not provide the level of benefits I would be expecting	
	PR4	I am worried about the diagnostic errors that would be caused by AI-based ICDDSS	Self-developed based on qualitative study
	PR5	I believe the emerging AI-based ICDDSS are not technically mature so far.*	Adapted from [54]
Medico-legal risk	LR1	I'm concerned that the present liability laws will hold the doctor responsible for any harm/injury arising from an incorrect diagnosis decision suggested by AI-based ICDDSS.	Self-developed based on [96] and qualitative study
	LR2	I am concerned that the present liability laws do not adequately protect doctors from the potential risks (injury/harm to the patient, litigations) arising from the use of AI-based ICDDSS.	
	LR3	I'm worried that in case of injury or harm to the patient (resulting from the use of AI-based ICDDSS), the present liability laws are not clear on who will bear the damages.	
	LR4	I'm concerned that the manufacturers try to shield themselves from legal liability of harm/injury (resulting from the use of AI-based ICDDSS) through product disclaimers.*	
Inertia	IN1	Even if AI-based ICDDSS is available, I will continue using my existing method (without AI assistance) to diagnose because it would be stressful for me to make changes	Adapted from [26,99]
	IN2	I will continue using my existing method (without AI assistance) to diagnose simply because I have done so regularly in the past.	
	IN3	I will continue using my existing method (without AI assistance) to diagnose even when I know that this may not be the best (most efficient/most effective) way to do it	
Perceived threat	PT1	I think using AI-based ICDDSS for a long time would lead to a gradual deterioration of my skill and ability to diagnose	Self-developed based on qualitative study
	PT2	I am worried that technicians or doctors (non-specialists) will be able to replace the role of specialist doctors with the help of AI-based ICDDSS in the future.	Self-developed based on qualitative study
	PT3	I believe advances in AI-based ICDDSS technology would lead to unemployment for some doctors in the future	Adapted from [22]
	PT4	I believe AI-based ICDDSS technology is likely to replace the role of doctors in the future	
	PT5	I think using AI-based ICDDSS for a long time would make doctors dependent on them	
Resistance to change	RC1	I don't want the AI-based ICDDSS to change the way I make clinical decisions	Adapted from [28]
	RC2	I don't want the AI-based ICDDSS to change the way I diagnose	
	RC3	Overall, I don't want the AI-based ICDDSS to change the way I currently work	
Behavioral intention to use	BI1	I would like to use AI-based ICDDSS if I have an opportunity	Adapted from [70]
	BI2	I intend to use AI-based ICDDSS in my practice when it becomes available in my department or hospital.	
	BI3	Given an opportunity, I predict that I will use AI-based ICDDSS to assist me in diagnostic decisions	

Notes: * items removed from the analysis due to poor loadings (<0.708).

APPENDIX D, Common Method Bias Analysis

Construct	Item	Factor path/loading (R_1)	R_1^2	T-value	Method path/loading (R_2)	R_2^2	T-value
BI	BI1	0.877**	0.769	15.375	0.019	0.000	0.287
	BI2	0.878**	0.771	13.395	0.009	0.000	0.131
	BI3	0.906**	0.821	14.494	–0.029	0.001	0.411
DT	DT1	0.845**	0.714	28.42	0.027	0.001	0.571
	DT2	0.925**	0.856	46.078	–0.077*	0.006	2.118
	DT3	0.823**	0.677	20.797	0.052	0.003	0.995
EE	EE1	0.853**	0.728	19.531	–0.026	0.001	0.47
	EE2	0.800**	0.640	18.997	0.027	0.001	0.493
	EE3	0.868**	0.753	21.589	0.000	0.000	0.001
IN	IN1	0.795**	0.632	18.294	–0.063	0.004	1.185
	IN2	0.913**	0.834	27.233	0.016	0.000	0.342
	IN3	0.885**	0.783	25.504	0.045	0.002	0.946
LR	LR1	0.854**	0.729	27.202	–0.036	0.001	0.841
	LR2	0.851**	0.724	22.002	0.019	0.000	0.32

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Construct	Item	Factor path/loading (R_1)	R_1^2	T-value	Method path/loading (R_2)	R_2^2	T-value
	LR3	0.754**	0.569	12.038	0.023	0.001	0.309
PE	PE1	0.911**	0.830	12.866	−0.079	0.006	0.923
	PE2	0.736**	0.542	9.222	0.060	0.004	0.677
	PE3	0.738**	0.545	10.159	0.125	0.016	1.527
	PE4	0.895**	0.801	11.294	−0.138	0.019	1.529
	PE5	0.830**	0.689	12.563	0.020	0.000	0.276
PR	PR1	0.857**	0.734	13.5	0.134	0.018	1.728
	PR2	0.946**	0.895	21.545	0.204**	0.042	3.507
	PR3	0.607**	0.368	8.003	−0.278**	0.077	3.65
	PR4	0.792**	0.627	17.593	−0.032	0.001	0.626
PT	PT1	0.733**	0.537	12.168	−0.026	0.001	0.349
	PT2	0.736**	0.542	13.128	−0.074	0.005	1.215
	PT3	0.810**	0.656	17.38	0.018	0.000	0.274
	PT4	0.811**	0.658	15.596	0.081	0.007	1.233
	PT5	0.837**	0.701	19.903	0.006	0.000	0.112
RC	RC1	0.853**	0.728	14.717	0.013	0.000	0.197
	RC2	0.906**	0.821	20.038	0.054	0.003	0.951
	RC3	0.787**	0.619	13.611	−0.068	0.005	1.004
SI	SI1	0.801**	0.642	17.59	0.099	0.010	1.784
	SI2	0.847**	0.717	21.935	0.029	0.001	0.576
	SI3	0.873**	0.762	14.866	−0.157*	0.025	2.232
TR	TR1	0.819**	0.671	10.885	−0.017	0.000	0.203
	TR2	0.793**	0.629	11.392	0.059	0.003	0.736
	TR3	0.716**	0.513	8.478	0.062	0.004	0.661
	TR4	0.797**	0.635	10.56	0.034	0.001	0.394
	TR5	0.976**	0.953	16.538	−0.133	0.018	1.9
Average		**0.831**	**0.6953**		**0.00005**	**0.0071**	

Notes: $^*p < .05$; $^{**}p < .01$.

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