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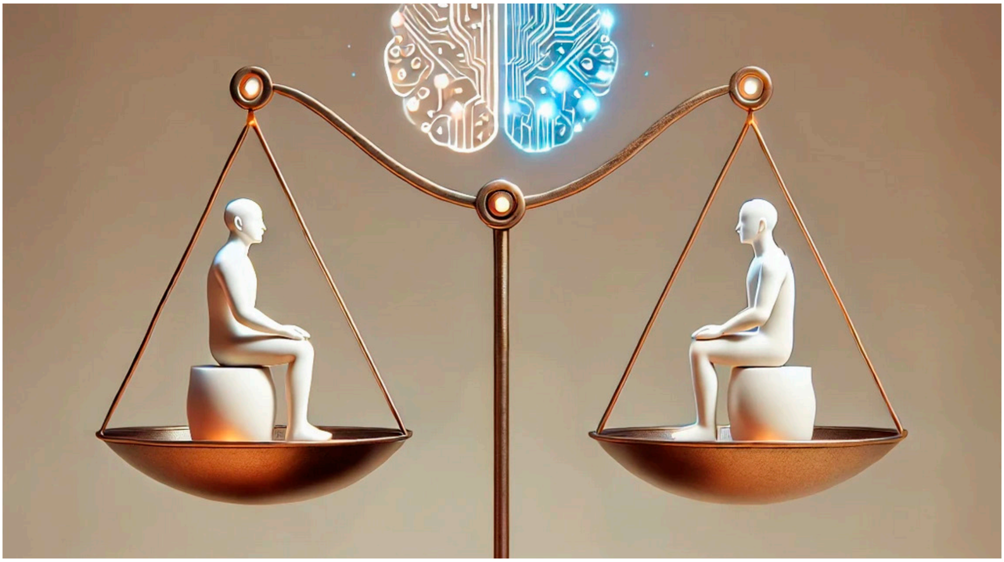

Utility of AI-based decision support systems in mental health: Needs and challenges for shared decision-making

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Abstract

Mental healthcare services have been put under pressure from the demands of the increase in the prevalence of mental health problems. The rapid development of technologies, such as Artificial Intelligence (AI), in healthcare provides significant opportunities for the mental health services, including an improvement in clinical decision-making. However, the implementation and integration of AI-based decision support systems (DSSs) into mental healthcare present concerns regarding its sustainable use, which potentially may conflict with decision-making workflows, communication with the patient, and shared decision-making (SDM) processes.

The main objective of this thesis is to explore the role of AI-based DSSs in mental healthcare, with a specific focus on the requirements for integrating shared decision-making (SDM) principles into these systems.

The thesis is based on a combination of two studies. The first is a scoping review with the aim of examining the empirical evidence regarding the use of AI-based DSSs in current research and how these systems have been researched, implemented, and evaluated in relation to the support of decision-making. This study included twelve studies that examined AI-based DSSs in healthcare, self-care, and simulation settings. The findings identified AI-based DSSs with a variation of utility, including the support for diagnosis and prediction of mental health state, treatment selection, and self-help for individuals seeking care. These AI-based systems had diverse data flows and a range of end-user interface interactions, which contributed to observable variations of decision-making processes. The evaluation of these AI-based systems revealed challenges, including their accuracy, workflow alteration, trustworthiness, and patient-healthcare professional communication when looking at the three factors of human, organization, and technology.

The second study is a qualitative study, with semi-structured interviews with the aim of exploring the requirements for using AI-based DSSs in mental healthcare from the healthcare professionals' perspective and grounded in a shared decision-making framework. The findings showed that healthcare professionals emphasized the need for AI-based DSSs in relation to supporting early detection, holistic assessments, and a flexible healthcare approach in triage and personalized treatment recommendations. However, concerns were raised about inaccuracies in interpreting non-verbal cues, risks of overdiagnosis, reduced clinician autonomy, and missing human interaction with more use of AI that may lead to unseen problems such as a weakened trust in the therapeutic relationships.

The key findings of this thesis are: (1) research on AI-based DSSs in mental health is in a pre-implementation stage, with no studies examining post-implementation adoption in clinical processes, (2) several potential implementation barriers and facilitators identified in relation to human, organization, and technology fit framework for the three AI types in the scoping review, with a significant gap of studies focusing on organization factor, (3) none of the literature in the scoping review explored SDM as a process when using or adopting AI-based DSSs in clinical workflows, (4) needs and concerns related to SDM elements were emphasized by healthcare professionals in all major categories of the SDM integrative model (essential, ideal, and general). However, SDM as a distinct and explicitly defined concept in healthcare practice was not illustrated by healthcare professionals.

In conclusion, the research on AI-based DSSs is still in its infancy stage, needing more empirical studies to evaluate the impact of these systems on the decision-making processes and closing the gap of missed SDM empirical investigation. When investigating SDM, it is crucial to consider both implicit and explicit representations of SDM to help derive meaningful research outcomes for the design and implementation of AI-based DSSs in future research.

Keywords: Artificial intelligence, mental health, shared decision-making, implementation, decision support systems, healthcare professionals, and young adults.

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List of scientific papers

Study 1

Auf, H., Svedberg, P., Nygren, J., Nair, M., & Lundgren, L.. The use of artificial intelligence in mental health services to support decision-making: Scoping review J Med Internet Res 2025;27:e63548. doi: 10.2196/63548.

Study 2

Auf, H., Lundgren, L., Nygren, J., Lena Petersson, & Svedberg, P.. Healthcare Professionals' Perspectives on AI-Driven Decision Support in Young Adult Mental Health: An analysis through the lens of a shared decision-making framework. [Submitted to Frontiers].

Abbreviations

AI	Artificial Intelligence
CBT	Cognitive behavioral therapy
DSS	Decision support system
DL	Deep learning
HCAI	Human-centered AI
HCI	Human-computer interaction
HOT-fit	Human organization technology - fit
ML	Machine learning
NLP	Natural language processing
PRISMA-ScR:	Preferred Reporting Items for Systematic Reviews and Meta-Analyses
RCT	Randomized controlled trial
RQ	Research question
TRL	Technology readiness levels
SDM	Shared decision-making

1 Introduction

Artificial intelligence (AI) has rapidly advanced across various industries including healthcare in the past few years, where efforts are made to apply it in supporting clinical workflows, decision-making processes, coordinating care, and administrative tasks (Maleki Varnosfaderani & Forouzanfar, 2024; Secinaro et al., 2021). Several AI-based systems and models are being developed to aid decision-making in healthcare. However, studies illustrate the need for investigating how these tools can impact practical integration in workflows, particularly in areas such as clinical engagement, trust, and the communication between patients and healthcare professionals (Higgins et al., 2023; Triberti et al., 2020).

Mental healthcare is facing significant challenges in Sweden, as in many other European countries, due to the rising prevalence of mental health problems over the last decades (Blomqvist et al., 2019; Hagquist et al., 2019; Potrebny et al., 2017). These challenges place a considerable strain on healthcare systems, increasing health and economic demands, affecting individuals seeking care, and the ability to maintain healthcare services to meet the growing demand. Mental health disorders account for approximately 31% of the overall Disability-Adjusted Life Years (DALYs) for people aged between 10-24 years old (IHME, 2021). The burden seems to continue to grow, with no indication of slowing down (Brunette et al., 2023; Daly et al., 2022; Potrebny et al., 2024).

Delays in early interventions, treatment, and recurring episodes of mental health problems during adolescence are worrying, as they significantly increase the likelihood of poor long-term outcomes and raise the risk of developing complex, chronic mental health disorders in adulthood (De Girolamo et al., 2012; Patton et al., 2014). Research suggests that governments should prioritize investment in mental health services, because of the high demand and the low level of preparedness of the healthcare sectors in dealing with this growing need (Malla et al., 2018). Strengthening the mental health systems is therefore critical for mitigating the increase in the burden of mental health services (Santomauro et al., 2021).

Efforts are continuously being made to address the growing demand for mental healthcare by implementing and adopting digital systems powered by AI. Such systems aim to support both the healthcare professionals and the patients throughout the mental healthcare journey, including key procedures such as prevention, diagnostics, and treatment (Lovejoy, 2019; Olawade et al., 2024).

Moreover, AI has created opportunities to enhance personalized care with the advantage of offering more sustainable mental healthcare, ensuring that interventions are tailored to each patient's unique needs and preferences (Graham et al., 2019). However, despite these possible benefits, concerns have been raised about how AI systems align with the principle of person-centred care and whether they could inadvertently hinder meaningful patient engagement and shared decision-making between the patients and the healthcare professionals (Bjerring & Busch, 2021; Triberti et al., 2020).

The decision-making process in healthcare has continuously evolved to empower patients to take an active role in their own care. Research has illustrated benefits from patient involvement in the healthcare process, advocating a shift from disease-centred care to person-centred care (Green et al., 2002; Murgic et al., 2015). Shared decision-making (SDM) is a widely recognized clinical approach that embodies this shift, emphasizing collaboration between patients and healthcare professionals to make informed decisions that align with patients' values, preferences, and individual context (Chen et al., 2023). This approach acknowledges that patients are experts in their lived experiences, while healthcare professionals contribute their clinical expertise to facilitate a personalized decision-making process.

Given the growing integration of AI in healthcare, it is crucial to explore how SDM can be effectively maintained and adapted in AI-supported mental health contexts. Understanding how AI can complement rather than compromise involvement and decision-making processes is essential to ensure that technological advancements continue to support patient autonomy and personalized care. However, there is a lack of research on the practical implementation of AI systems and how SDM principles can be effectively integrated into their use (Abbasgholizadeh Rahimi et al., 2022; Khosravi et al., 2024; Nilsen et al., 2024). This thesis seeks to address this gap by exploring the requirements of the implementation and utility of AI-based decision support systems (DSSs) in mental health services with a particular focus on SDM integration.

2 Previous research

2.1 Shared decision-making in healthcare

The Patient Act law 2014 (Chapter 7) in Sweden grants patients the right to be informed and included in making a choice between their treatment options when there are alternative options of care (Riksdagen, 2014). However, the current state of SDM in mental health is disconnected from the needs and experiences of healthcare professionals and patients (Chmielowska et al., 2023). Engaging the patients in the decision-making process regarding their own care has demonstrated positive effects, including improved quality of care, better health outcomes, increased patient satisfaction, and potential reduction of costs (Hughes et al., 2018; Katz & Hawley, 2013; Veroff et al., 2013). Additionally, it benefits the healthcare professionals in knowing what works best for the patients from the patient's perspective as experts in their own situation (Alegria et al., 2018; Krist et al., 2017). However, individuals with mental illnesses often express a desire to be more involved than they are allowed to be (Adams et al., 2007; Beitinger et al., 2014), young adults, for example, desire more engagement in SDM in talking therapies, particularly when deciding on a treatment direction (Lovén Wickman & Schmidt, 2023). Despite the desire to be involved, and the recognized benefits of SDM, its integration into mental health services faces several challenges, including the lack of available quality support tools, adjusting to the patient's ability, barriers to SDM integration in designed interventions, and the need for change in the decision-making culture when SDM is implemented (Beitinger et al., 2014; Kalsi et al., 2019; Slade, 2017).

Involving the patients in decision-making can be done in different styles, including active (high involvement), passive (minimum involvement), or shared involvement (Aziz, 2023). The different styles of decision-making can affect both the patients and healthcare outcomes differently. Cosh et al. (2017) looked at these three types of patient involvement in clinical decision-making. The study showed that preference for shared patient involvement in clinical decision-making was associated with lower healthcare costs and shorter duration of admission, in addition to being associated with a potential increase in patient satisfaction compared with the active patient involvement style. The supportive strategies and techniques to promote SDM include a variety of tools and methods, including decision aids, communication techniques, patient education, and personal skills of healthcare professionals (Cheng et al., 2017; Zisman-Ilani et al., 2017). However, for these methods to be effective, it is essential that SDM is systematically prepared for and embedded within the healthcare environment and services. In addition to the importance of evaluating the needs for SDM to align with end-users and organizational perspectives (Elf et al., 2015; Waddell et al., 2021).

The increasing use of technology and the emerging body of research on digital health and SDM indicate a promising potential for digital tools to support conventional SDM processes in mental healthcare (Vitger et al., 2021). However, evidence shows that the need for technical support and the challenges to patient and healthcare professional relationships can act as barriers to the effectiveness of these technologies thus requiring further investigation (Korsbek & Tønder, 2016). From the standpoint of clinical workflows and end-users, AI-based systems present several unique advantages to the ways of working in mental healthcare, including personalized decision-making, and enhanced communication between patients and healthcare professionals, which contribute to supporting SDM (Lee et al., 2021; Sauerbrei et al., 2023; Viswanathan et al., 2022). However, concerns have been raised by both healthcare professionals and patients regarding the widespread efforts to develop and adopt AI to support decision-making in healthcare, underscoring the potential challenges facing the acceptance of change in the ways of working and loss of autonomy (Khanijahani et al., 2022). Healthcare professionals have expressed reservations about integrating AI-based DSSs into decision-making processes, given the challenges concerning, for example, accepting AI-based second opinions (Viswanathan et al., 2022).

The growing evidence of challenges and concerns surrounding the use of AI and SDM emphasizes the need for a deeper understanding of how AI technology can be integrated, presented, and used within the context of SDM in mental healthcare practice.

2.2 The role of AI-based decision support systems in mental healthcare

There are continuous efforts being made to address the high level of demand for mental health services. Research has been increasingly investigating the development and use of AI to support both healthcare professionals and patients in the mental healthcare journey, particularly in procedures such as prevention, diagnostics, and treatment (Lovejoy, 2019; Olawade et al., 2024).

AI-based DSSs are equipped to enhance healthcare and self-care processes. Moreover, these systems show promise for bridging the gap between healthcare and self-care by facilitating the exchange of information across both domains (Ji et al., 2021). From a healthcare viewpoint, AI-based DSSs have the potential to shift mental healthcare towards more person-centred approaches by supporting personalized treatment choices based on the individual's needs (Graham et al., 2019). However, with this optimistic view on the potential role of AI in mental health. Graham et al. (2019) emphasized the need to bridge the gap between AI in research and its application in mental health clinical workflows to avoid the negative effects of the potentially misleading promise from early AI development.

The potential utilization of AI-based DSSs has particular significance in the context of mental healthcare, given the challenges in the identification and management of mental health problems faced by contemporary mental health services. However, the complex and heterogeneous nature of mental health problems presents considerable obstacles for AI-based DSSs in delivering accurate diagnostics, effective treatment guidance, and tailored interventions. Although it has been found that AI systems currently demonstrate greater efficacy in aiding the identification of symptoms of mental health problems than diagnosing specific disorders (Abbasgholizadeh Rahimi et al., 2022; Lee et al., 2021; Sauerbrei et al., 2023; Triberti et al., 2020; Viswanathan et al., 2022; Yan et al., 2022).

The integration of AI technology into decision-making introduces AI as a third key actor alongside healthcare professionals and patients. This new triad raises concerns about the shifting dynamics of power among the three actors and a potential shift of decision-making toward a paternalistic approach (Kühler, 2022; Lorenzini et al., 2023; McDougall, 2019). There is thus a pressing need to explore how AI can be used in decision-making and influence various aspects of it including clinical engagement, shared decision-making, and patient-physician communication within the mental health field (Higgins et al., 2023; Triberti et al., 2020).

Despite the potential promises and inherent challenges associated with AI systems in supporting decision-making processes within mental healthcare, there remain notable research gaps concerning their practical utility. Fundamental questions persist regarding the types of decisions AI systems can support in real-world environments, the extent to which these systems engage patients in the decision-making process, and the methodologies employed for their evaluation. While extensive research has examined the performance, proof of concept, and ethical considerations of potential applications of AI, there remains a notable gap in the literature regarding the integrative and empirical use of AI systems in healthcare processes (Grzenda, 2021; Shatte et al., 2019; Warrier et al., 2023).

2.3 Implementation of AI-based decision support systems in mental health services

AI-based systems are continuously being developed for potential future use in mental healthcare (Bertl et al., 2022; Maslej et al., 2023; Russ et al., 2019; Tutun et al., 2022). The implementation of AI systems can be viewed as a process starting from early efforts during the research and development phases (Y. Park et al., 2020; Svedberg et al., 2022). These initial efforts are followed by more practical implementation phases, which take place in the intended context and environment of use. The later phases of implementation can involve: (1) organizational planning for assessing the healthcare integration and use of AI and the potential consequential changes and needs; (2) practical change that occurred when implementing the AI system in practice; (3) post-implementation efforts for sustaining the use of the implemented AI system (Nair et al., 2024).

It is essential to address the end-user's considerations, needs, and concerns, while also anticipating potential usability challenges in the early stages of planning for implementing a newly designed AI system. Ensuring that AI systems align with user expectations and facilitate seamless integration into clinical workflows can participate in enhancing the possibility of successful AI adoption (Beltrao et al., 2022; Thieme et al., 2023; Nair et al 2024). From a development perspective, an extensive body of literature illustrates the importance of explainable AI (XAI), a concept that emphasizes the need for AI methods to enable the users to understand the decision-making methodology behind the model output (Pawar et al., 2020). Failing to do so may lead to a black-box issue, meaning that the decision-maker would not be aware of the reasoning behind the AI system leading to an inability to track the problem source, and potentially reducing the autonomy and trust of the decision-makers (Amann et al., 2020). From a wider perspective, AI systems are gradually transforming society, including healthcare (Bajwa et al., 2021). There is thus a need for healthcare practice to have processes in place to be able to utilize the benefits of AI in clinical processes and avoid disturbances affecting healthcare staff or current decision-making processes (Minerva & Giubilini, 2023).

Concerns have been raised that AI may conflict with patient involvement in relation to the integration of AI systems in healthcare processes, potentially leading to a conflict with the core ideals of person-centred care (Bjerring & Busch, 2021). One challenge that may arise when AI is being used to support decision-making in clinical workflows is that the AI output could interfere with the patient-healthcare professional relationship and communication. This may lead to several challenges, including organizational issues of delaying and creating uncertainties in making a decision (decision paralysis), potential communicational issues in interpreting AI outputs, and socio-relational issues leading to confusion over roles and responsibilities for finalizing decisions (Triberti et al., 2020).

Given this context, it becomes imperative to understand the interplay between the complexities of mental health problems and AI-based DSSs mechanisms, emphasizing the importance of incorporating the perspectives of end-users and real-world use. Such an inclusive approach is essential for guiding the effective implementation of AI-based systems in mental health settings (Golden et al., 2024). Numerous studies underscore the necessity for a nuanced understanding of AI-based system usage within real-world mental healthcare to inform future implementation strategies (Bertl et al., 2022; Espejo et al., 2023; Yin et al., 2021).

Concerns are presented in the literature about the future potential long-term use of AI-based decision support in healthcare, where it is maintained that SDM could be at risk, potentially moving toward more paternalistic decision-making that excludes patients (Lorenzini et al., 2023; McDougall, 2019). Considering SDM should thus be done when introducing AI as a new technology in the decision-making processes. McDougall (2019) argues that if AI is designed and implemented with the consideration of patient engagement, it has the potential to support SDM rather than hinder it.

Research into the implementation of AI-based DSSs in the context of SDM is still in its nascent stages, emphasizing the need for further exploration into how AI can effectively support SDM processes in the future and how AI-based DSSs can be implemented (Abbasgholizadeh Rahimi et al., 2022; Graham et al., 2019; Higgins et al., 2023).

3 Study rationale and aim

Previous research emphasizes the critical need to involve patients in decisions affecting their health through SDM practices in mental healthcare. This approach is important for improving patient outcomes, ensuring person-centred care approaches, and enhancing the quality and effectiveness of care (Joosten et al., 2008; Shay & Lafata, 2015; Thomas et al., 2021). Rapid advancements in AI development in mental health presents significant potential for supporting decision-making. However, research shows that poorly designed and implemented AI systems can unintentionally reinforce paternalistic decision-making, disrupt care workflows, and pose other challenges that undermine or conflict with the core principles of SDM (Bjerring & Busch, 2021; Triberti et al., 2020).

The process of SDM is initiated well before the patient reaches the consultation room; it starts when the patient first presents with the problem and seeks support. It is therefore evident that SDM needs to be systematically integrated into care workflows, service design, and digital systems from the early stages of implementation of healthcare services (Drake et al., 2009; Griffioen et al., 2017). This integration is particularly important when introducing AI-based tools, because of the risk that such technologies may inadvertently marginalize the patient's voice in decision-making.

Despite the growing interest in using AI to support decision-making in mental healthcare, there remains a significant gap in research regarding how to effectively implement AI systems for this purpose while embedding SDM-supporting approaches and end-user perspectives into the design of care processes (Carr, 2020; Koutsouleris et al., 2022; Triberti et al., 2020; Wilson et al., 2023). This thesis seeks to address this gap by exploring how AI-based DSSs can be implemented to include and potentially enhance SDM, ensuring that both technological advancements and patient-centred approaches work collaboratively to improve outcomes in mental healthcare.

Aim

The overall aim of this thesis is to explore the role of AI-based decision support systems (DSSs) in mental healthcare, with a specific focus on the requirements for integrating shared decision-making (SDM) principles into these systems.

The specific aims for the included studies are outlined in Table 1.

Table 1. Overview of aims for the two studies.

Study	Aim
Study 1	To explore the empirical evidence for the use of AI-based DSSs in supporting different types of decisions in mental health. This includes how AI-based DSSs has been researched, applied, and evaluated for use and implementation.
Study 2	To explore the requirements for using AI-based decision support systems in mental healthcare from the healthcare professionals' perspective and grounded in a shared decision-making framework.

4 Theoretical perspective and central concepts

In this chapter, the theoretical foundations of participation, SDM, empowerment, AI-based DSSs, and implementation are explored to provide an understanding of key concepts in relation to the adoption and sustainable use of AI-based DSSs in mental healthcare. The illustration of the concepts begins with participation and its relationship with empowerment, exploring their role in enabling individuals to engage actively in their own care. SDM and its relation to person-centred care are then discussed, emphasizing how AI-based DSSs can support SDM, which is followed by an exploration of AI-based DSSs in relation to mental healthcare and SDM. Finally, the concept of implementation is explored, outlining critical factors for the successful adoption and long-term integration of AI-based DSSs in mental healthcare. This thesis is grounded in these perspectives and concepts, which have inspired the choice of research questions, methods, and data analysis approaches.

4.1 Participation and Empowerment

Patient participation is increasingly recognized as a fundamental aspect of healthcare, as it enhances care quality and contributes to improved patient health outcomes (Coulter, 2012; Hibbard & Greene, 2013). From a societal perspective, this concept parallels Arnstein's Ladder of Citizen Participation (1969), which demonstrates how varying levels of individual engagement—from informing and consultation to partnership and full delegation of power—result in different degrees of empowerment through participation (Castro et al., 2016). Patient participation and inclusion in healthcare are fundamental to the person-centred care approach, which actively involves patients in both the design and delivery of healthcare services, as well as in their own care decisions through SDM as illustrated in the framework of McCormack and McCance (2006). However, more participation does not always lead to a higher level of empowerment (Tritter & McCallum, 2006). The need to address the alignment between participation, empowerment, and shared decision making has thus been emphasized in the research literature (Ocloo & Matthews, 2016). From a theoretical perspective, SDM aims to bridge the gap between patient participation as a necessity and empowerment as an outcome, positioning itself between paternalistic healthcare models and full patient autonomy (Kon, 2010; Légaré et al., 2018; Straub et al., 2008).

Empowerment, in turn, can lead to better patient participation in healthcare by enabling individuals to be in a more active and informed state (Artino Jr., 2012; Powers & Bendall, 2004; Thiruvengadam et al., 2016). Being empowered as an outcome of participation can be reflected in the patient's ability to engage in informed discussions, negotiate care preferences, and adopt self-directed health behaviors (Aslani, 2013). Empowerment outcomes for the individual can be seen in three levels according to the theory of empowerment by Zimmerman (1995, 2000): (1) better personal control and self-efficacy (interpersonal component), (2) greater critical awareness within the environment (interactional component), and (3) acting on addressing topics important to the individual (the behavioural component). Several studies show that this enhanced sense of control and responsibility leads to better adherence to treatment, partnership dynamics between the patients and healthcare professionals, and greater patient satisfaction (Hibbard & Greene, 2013; Náfrádi et al., 2017). SDM has been described as a key approach to improve patient participation and empowerment in healthcare services, ultimately contributing to the advancement of person-centred healthcare practices (Chen et al., 2023; Shay & Lafata, 2015). Building on this understanding, this thesis focuses on the use and implementation of AI-based DSSs in mental health services, with a particular emphasis on integrating SDM into these systems.

4.2 Shared decision-making

SDM is a key concept for engaging individuals in their own care during clinical decision-making. SDM is commonly researched in the literature as both a practical process that occurs between individuals in healthcare and a collaborative value approach to be implemented in healthcare processes (Drake et al., 2009; Scholl & Barr, 2017). From a practical viewpoint, according to Frosch and Kaplan (1999), SDM is a process in which the patient is actively participating in their care decisions during the interaction with the healthcare. Healthcare professionals provide information, treatment options, and outcome probabilities that enable both parties to make a mutual decision.

The concept of SDM is described in various ways in the literature, reflecting its complexity and the different contexts in which it is applied. I utilize the framework proposed by Makoul and Clayman (2006) in this thesis, who present SDM into three elements: *essential, ideal, and generic*. This clustering is valuable as it provides a nuanced understanding of SDM, capturing its core elements while also considering its practical applications across different contexts. This can help with the efforts of planning for the implementation and integration of SDM in healthcare services. The essential elements, according to Makoul and Clayman (2006), are practical or clinically oriented and required in the interactions between the healthcare professional and the patient, which can help with examining the practical required elements of SDM to be enabled in the healthcare services, such as explaining the problem and options that have clear pros and cons to be communicated. The ideal elements are more optional practical elements that are important but not necessary to be included in the SDM steps, such as providing unbiased information or presenting evidence. The generic elements are value or quality-based approaches that can influence the application of SDM in clinical practices and service development, allowing the assessment and improvement of SDM quality in healthcare services. General elements include, for example, patient education, information exchange, and patient participation. The elements can be seen in Appendix A.

SDM is often described as an approach that requires careful preparation and early integration into healthcare services to ensure it is ready for practice (Griffioen et al., 2017; Scholl & Barr, 2017). A key element in this preparation is the use of decision-support tools, which play a foundational role in facilitating SDM by providing the necessary framework for both patients and healthcare providers to engage in informed, mutual decision-making (Slade, 2017). However, despite their suggested role, there remains limited understanding of how AI-based decision-support tools can be effectively utilized to support SDM in healthcare.

4.3 Artificial intelligence-based decision support systems

AI-based systems in healthcare are often defined in the literature either according to their outcomes to be perceived as intelligent from the healthcare perspective (executing tasks that require human intelligence) (Secinaro et al., 2021), or as systems with complex algorithmic programming that resemble human intelligence from a computer science perspective (Sheikh et al., 2023). If only the external or internal boundaries of the AI are followed regarding the definition of its intelligence problems can be created when assessing it. AI in healthcare is thus understood in this thesis as the development and application of computer systems capable of performing tasks that typically require human cognitive intelligence. Furthermore, with the additional requirements that these systems utilize advanced computational methods, such as machine learning (ML), deep learning (DL), computer vision, or other AI methods, to analyse complex medical data and support various healthcare tasks. In conclusion, for AI-based DSSs to be recognized as intelligent systems, they must demonstrate underlying technological complexity and be perceived as intelligent by end-users from a human perspective (i.e. perceived as AI from both internal and external perspectives).

The implementation of AI-based tools in healthcare for decision-making support involves overlapping concepts that require clarification. Digital healthcare systems refer to any digital services integrated or used in healthcare, including telemedicine, medical devices, and DSSs, among other digital systems (Ronquillo et al., 2017). DSSs can be described within this broad category as computer programs designed to assist decision-making processes where and when it is needed (Moreira et al., 2019). These systems use various programming technologies including artificial intelligence. However, it is important to note that not all DSSs are AI-based, and conversely not all AI-based healthcare technologies are DSSs. In relation to the above, the focus in this thesis is thus on AI-based DSSs.

The term clinical decision support systems (CDSSs) commonly used to refer to similar AI-based systems designed for clinical (healthcare specific) use as referred to in literature alternatively to the term DSSs. The latter is used in this thesis to avoid restricting the scope to AI systems used solely by clinicians, thereby including potential systems designed for patient use and non-clinical healthcare professionals (Moon & Galea, 2016). This broader definition of DSSs allows for the inclusion of AI systems designed for both healthcare and self-care applications within the broader domain of mental health.

4.4 Implementation process

Achieving successful implementation requires careful planning, including system development, design, and structured implementation efforts to prepare the AI-based DSSs for practical use in mental healthcare settings (Nair et al., 2024). Various definitions of implementation are described in the literature. Implementation refers in this thesis to "*The process of putting a defined practice or program into practical effect; to pursue to a conclusion*" (Fixsen et al., 2005, p. 81). This definition involves deliberate and planned efforts to introduce new interventions in real-world service settings, aiming to improve service delivery and health outcomes, with a focus on ensuring sustainable use (Fixsen et al., 2005, 2009). Implementing digital services in mental healthcare is complex, requiring a thorough understanding of technological maturity and the involvement of diverse stakeholders throughout the process (Nilsen et al., 2022). Assessing the development and readiness levels of AI-based DSSs is crucial before deployment, and it is thus essential to define system maturity and readiness evaluating implementation.

One approach for assessing maturity, which I have used in my thesis, is the technology readiness level (TRL) framework (Mankins, 1995). TRL is a systematic methodology that evaluates the readiness of a particular technology to be launched in its intended context. It categorizes the maturity into nine phases, ranging from the early research phase to fully tested and operational systems. This framework allows the evaluation of systems that fall in the same maturity level, to create meaningful understandings. I focus in my thesis on AI-based DSSs with TRL levels six and above. These systems have been demonstrated or prototyped in real-world contexts, with TRL 6 representing systems that have been validated in relevant environments, and higher levels indicating full integration and operational status. Although there is limited research on the practical application of AI-based tools in healthcare, I chose to focus on tools with TRL levels above six because they provide a more advanced stage of development and practical relevance. By examining systems that are already integrated or nearing full implementation, this approach allows for a deeper understanding of how these tools can be effectively utilized in real-world decision-making scenarios and their potential to drive meaningful improvements in healthcare practices.

Another approach is to evaluate the use and implementation of information technologies in healthcare, an area that presents several models and frameworks available for guidance (Sligo et al., 2017). However, many of these frameworks may fall short by focusing on either technological or organizational aspects, not accounting for the social and human perspectives. The human, organization, and technology framework (HOT-fit) presented by Yusof et al. (2008) is an integrative framework for health information systems that expands knowledge to include human factors. It is designed to evaluate the effectiveness and potential challenges of health information systems by considering the interplay between three essential components: the human factor focusing on the individual user experience of the information system including user behaviors and satisfaction, the organization factor which focuses on the structure and environment evaluation of use., the technology factor focuses on the functionality of the technical parts of the system, in addition to the quality of information provided by the AI system. These three factors of the framework consist of sub-categories or dimensions, and each dimension includes several elements that can be evaluated for each factor.

5 Methods

5.1 Ontological and epistemological methodological positioning

The ontological standpoint in this thesis assumptions is situated within a pragmatic paradigm in the spectrum between realism and idealism directions acknowledging the inherent complexities of integrating AI-based DSSs into mental healthcare (Bourgeault et al., 2010) This paradigm allows bridging the gap between the objective design and functionality of AI systems and the subjective experiences and interpretations of healthcare professionals engaged in SDM. AI is an ontologically complex concept, its further development poses challenges for comprehending its future evolution. As with the development of AI models the nature (ontological truth) of this concept is under development towards a more independent entity. For example, AI could hypothetically develop its own consciousness in the future leading to fundamental alteration of the way it is conceptualized in research (Butlin et al., 2023). This thus requires a continuous explorative understanding of AI as a concept that is under development, and it would be empowering to include end-users in this process of the concept combined with the development and implementation of the AI-based DSSs in context.

The epistemological approach in this thesis integrates both constructivist and post-positivist elements (Creswell, 2013). Constructivism according to Creswell (2013) emphasizes the co-construction of knowledge, and in this thesis, healthcare professionals' perceptions and experiences informed the understanding of AI-based DSSs implementation in mental healthcare context especially in relation to SDM. While post-positivism elements, on the other hand, included the thesis focus on more empirical and objective evaluations as conducted in the systematic analysis of available empirical data, and the interpretative approach of functionality of AI systems within the field of information systems (IS) (Walsham, 2006)(Walsham, 2006). By blending these perspectives, the research remains open to both objective inputs and subjective interpretations, fostering a dynamic interplay between theoretical frameworks and emerging insights in the field (Johnson & Onwuegbuzie, 2004; Morgan, 2007). The dual epistemological foundation approached in this thesis thus served in the nuanced exploration of the AI's role in SDM within mental health.

5.2 Methodological Overview

This thesis is based on two studies as illustrated in Table 2. The first study is a scoping review with a focus on the available empirical evidence on the topic, and the second study is an explorative qualitative study focusing on the healthcare professionals' needs of and concerns about AI-based DSSs in mental healthcare.

Table 2. Overview of the methods for the two studies in the licentiate thesis

	Study 1	Study 2
Design	Scoping review	Qualitative study
Data collection	Database search in five sources: PubMed, Scopus, PsycINFO, Web of Science, and CINAHL.	Semi-structured interviews
Sample	The search using keywords led to 1773 identified articles, 12 of which articles were eligible for the final analysis.	Healthcare professionals (N=15) with different roles: psychologists (N=6), nurses (N=5), welfare officers (managers) (N=3), social worker (N=1).
Analysis	Abductive analysis approach (Thompson, 2022).	Content analysis following deductive analysis approach (Graneheim et al., 2017; Lindgren et al., 2020).
Frameworks used	Clinical decision-making framework (Johansen & O'Brien, 2016) AI Input-process-output (Sarker, 2022) HOT-fit (Yusof et al., 2008)	SDM elements (Makoul and Clayman, 2006)
Research questions	RQ1: What are the characteristics of research on AI systems used in relation to support decision-making in mental health? RQ2: Which types of technologies, decisions, actors, and user flows of AI systems to support decision-making are described? RQ3: How were the AI-based decision support systems evaluated in research in the mental health context, and what discernible consideration might enable or hinder the adoption or implementation of these systems?	What are the needs and concerns for using AI systems to support decision-making in the care processes for healthcare professionals in mental healthcare?

5.3 Study 1

Study design

This study followed a scoping review approach with a study design guided by the five-phase framework by Arksey and O'Malley (2005). The phases included defining research questions, identifying relevant studies, selecting studies, charting data, and reporting results. The reporting process was conducted by following the PRISMA-ScR checklist (Preferred Reporting Items for Systematic Reviews and Meta-Analyses Extension for Scoping Reviews) (Tricco et al., 2018).

Identifying Relevant Studies

A search strategy was developed within the research team with the assistance of a librarian. Literature searches were carried out using the five main health research databases: PubMed, Scopus, PsycINFO, Web of Science, and CINAHL. Keywords used in the searches were guided by the following concepts and mesh terms: "mental health," "artificial intelligence," "decision-making," and "implementation.". The eligibility criteria for the studies were: peer-reviewed, empirical, published between 2011 and 2022, and focusing on the use of AI-based DSSs for mental health professionals or patients/individuals. The exclusion criteria were: articles not related to decision-making, non-empirical designs, and those with a Technology readiness levels (TRL) above 6 (i.e., systems or prototypes already demonstrated in relevant environment).

Study Selection (Screening)

The identified articles were first imported to EndNote to remove duplicates, and then the abstract-level screening phase was conducted using Rayyan, a web-based tool facilitating systematic teamwork. The researchers (HA and MN) read the abstracts and conducted regular follow-up meetings to ensure consistent application of the criteria in the initial screening phase. The full-text articles were then assessed by two team members during the second phase to screen and evaluate relevance to the eligibility criteria. Articles identified in the two phases, which the two researchers were uncertain about, were discussed by the full research team until a consensus was reached.

Charting the Data (Data Extraction)

A template sheet was used to extract data from each of the included articles regarding the characteristics of the research in order to address the first RQ. These included the author's name, publication date, title, aim, country, study design, care settings, mental health problems, and types of AI. A descriptive summary was performed to answer RQ1 about the characteristics.

Collating, Summarizing, and Reporting Results

RQ2-related findings were reported in three segments. (1) Categorizing AI systems according to their utility. (2) Mapping the relationship between the AI systems utility and the end-user interaction according to the types of interaction and decision-making process as described in the conceptual model by Johansen & O'Brien (2016), in which the decision-making process spans from situational awareness to decision execution. (3) Explorative analysis of the data flow and user interaction was conducted to draw the relationship between the end-user interaction and the AI system, in which the AI system components are as presented by Sremac et al. (2019).

An abductive approach guided by Thompson (2022) was used for the analysis of the findings for addressing RQ3. An inductive thematic analysis connecting emerged themes was first conducted, followed by a deductive approach using the framework of human, organization, and technology (HOT-fit framework) (Yusof et al., 2008). This framework allowed the assessment of the technology in relation to the end-users and the environment it is aimed to be used in. The framework consists of factors (human–organization–technology). There are sub-categories or dimensions under each factor, and each dimension includes several elements. Two additional elements, "trustworthiness" and "explainability", were found in the abductive analysis and were included in the framework and the analysis. The analysis was iteratively discussed between all the authors until consensus was achieved.

5.4 Study 2

Design

This study followed a qualitative study design using semi-structured interviews and a deductive content analysis approach (Graneheim et al., 2017; Lindgren et al., 2020). This approach integrated the elements of Shared Decision-Making (SDM) as predefined categories for analysis, based on the SDM framework by Makoul and Clayman (2006). The study adheres to the 32-item Consolidated Criteria for Reporting Qualitative Research (COREQ) (Tong et al., 2007).

Theoretical framework

The Makoul and Clayman (2006) framework categorizes SDM into three types of elements: essential, ideal, and general. (1) Essential elements refer to practical SDM steps necessary for clinician-patient interactions. (2) Ideal elements enhance SDM but are not mandatory to exist. (3) General elements focus on value-based approaches and processes of SDM that are quality based. All elements of the three categories can be seen in the Appendix A.

Participants

Participants were healthcare professionals with practice in mental healthcare and with professional experience working with young adults aged 18–30. A snowball sampling procedure was employed (Tong et al., 2007). A total of 16 healthcare professionals, of which 11 were women and 5 were men, participated in semi-structured interviews. The participants were employed as: psychologists (N=6), nurses (N=5), welfare officers (N=3), a social worker (N=1), and a physiotherapist (N=1), and were drawn from various clinical settings: primary care (n=9), youth guidance centres (n=4), student affairs support (n=2), and psychiatry (n=1).

Data collection

The data collection took place in semi-structured individual interviews, conducted either in person or digitally by research team members between October 2020 and February 2023. The interviews lasted from 34 to 57 minutes, and all were audio-recorded and transcribed verbatim. The interview guide included questions to focus on the healthcare professionals' views on the potential use of AI-based technologies in supporting decision-making, in addition to barriers, facilitators, and opportunities for integrating AI-based interventions into existing systems and processes.

Data analysis

A deductive content analysis guided by Graneheim et al. (2017, 2020) was used to explore the healthcare professionals' perspectives on AI use in relation to SDM. A codebook was developed with definitions and the operational use of SDM elements in the analysis.

To gain a comprehensive understanding of the content, the transcripts were read through thoroughly multiple times to become familiarized with the content and facilitate the coding process. A deductive approach using the SDM theoretical framework was then applied to identify meaning units linked to the participants' needs and concerns, which werecoded in terms of the three types of SDM elements. The meaning units were then condensed, categorized, and analysed to be finally reported as the identified needs and concerns. The iterative process of analysis was carried out collaboratively, with all authors reviewing and refining the findings. This collaborative effort ensured the results were accurately represented, validated, and adjusted for addressing the study aims.

5.5 Ethical considerations

The ethical considerations, related to the investigation of AI systems addressing mental health problems in this thesis, can be seen in two types: practical and research-related considerations. Saeidnia et al. (2024) illustrate three types of practical ethical considerations that can arise related to: the use of AI in a mental health context, the development and implementation of AI technology in mental healthcare, and considerations related to policies and recommendation guidelines of these solutions in society. Research-related considerations were carried out in Study 1, where a systematic approach following the PRISMA-ScR checklist was applied (Tricco et al., 2018) to ensure transparency and rigor throughout the review process. Ethical approval for engaging stakeholders in semi-structured interviews in Study 2 was granted by the Swedish Ethical Review Authority (Dnr 2020-06246), ensuring that the research was conducted in accordance with rigorous ethical standards.

The ethical principles outlined in the World Medical Association's Declaration of Helsinki (WMA, 2013), including the principles of autonomy, beneficence, non-maleficence, and justice, were followed in both the scoping review and the qualitative study to ensure the integrity and ethical approach. The following are reflections on the core ethical principles and on the thesis.

Autonomy

Informed consent was obtained from the healthcare professionals in Study 2. The participants were informed both verbally and in writing about the study's purpose, that they had the right to withdraw at any point of participation, and about how their data would be used prior to the interviews. They were also informed about the confidential and autonomous nature of participation. Confidentiality was ensured in all parts of the data collection and analysis process to protect the privacy and integrity of the participating healthcare professionals. The names and any details that can lead to the identification of the participants, such as workplace or address, were removed or coded to ensure autonomous participation.

Nonmaleficence

To ensure that the conducted research was not causing harm, the research questions and the nature of Study 2 did not concern the mental health problems of patients that the healthcare professionals engaged with. The questions were focused on the objective of investigating the use of AI and not on collecting any sensitive information about the patients, including personal experiences with patients, or any sensitive questions that may lead to divulging information about the identification of specific patients (Siriwardhana et al., 2013). Furthermore, no sensitive questions related to the healthcare professionals' profession or workplace, which may cause potential conflict with the workplace were included in order to minimize the risk of harm for the participants.

Beneficence

This research delves into an exploration of the evolving concepts of AI, SDM, and mental health, with the aim of generating valuable knowledge that can contribute to improving the quality of patient care. However, defining the direct and immediate benefits of this research for patients remains challenging, as the application of AI in mental healthcare is still in its early stages and undergoing rapid advancements. A National Health Service (NHS) report shows that the impact of AI applications in mental healthcare is expected to be seen in 3-10 years' time (Foley & Woollard, 2019). This thesis can thus help to pave the way for future benefits for patients in mental healthcare when AI is implemented and used in safe and sustainable measures.

Justice

The design in Study 1 included all types of AI-based DSSs targeting AI solutions used by individuals of all ethnic and socio-economic backgrounds, genders, and ages ensuring an inclusive approach to represent the diverse potential beneficiaries of the conducted research. Healthcare professionals from different professional backgrounds and genders were involved in Study 2, and all participants were treated with respect and fairness. Measures were taken to equally protect the participants' privacy and safeguard their well-being while conducting the interviews.

6 Results

6.1 Study 1

6.1.1 Overview and study characteristics

A total of 1773 articles published between 2011 and 2022 were identified in the literature search. Twelve articles were found to meet the eligibility criteria for the study after removing duplicates and applying the inclusion and exclusion criteria during the screening process. The included articles had a variety of study designs and primarily originated from the USA (n=7), followed by Canada (n=3), the UK (n=1), and China (n=1). The studies focused on three settings: healthcare, self-care, and simulation environments. The healthcare settings included primary care, emergency departments, and specialized mental healthcare. Self-care remote studies examined the use of AI-based DSSs using mobile applications and wearable sensors. Simulation studies were conducted in university-based psychiatry departments. The mental health problems that AI-based DSSs were targeting were depression (n=5), followed by substance misuse (n=2), autism spectrum disorder (n=2), suicide and mental health crises (n=2), and psychotherapy for various conditions (n=1).

6.1.2 Decision support utility, data flow, and user's interaction with the AI-based DSSs

Decision support utility

Three types of applications of AI-based DSSs were categorized according to their decision-support utility and the form of output they provide to support decision-making in mental health: (1) diagnostic and predictive AI including AI-based DSSs that provide support in the identification of mental health states with diagnostic/prognostic output in binary or categorical forms; (2) treatment selection AI, which comprise AI-based DSSs that present options for treatment with information explaining each option, designed to help healthcare practitioners and patients in the therapy selection process, and (3) self-help AI, the AI-based DSSs that were designed to support individuals in managing their own mental health, either within healthcare settings or remotely through self-care. All self-help AI systems were based on conversational agents and provided support for various mental health conditions using psychoeducation and behavioral therapy techniques. The three types of AI-based DSSs in mental health vary in the decisions they support, according to the level of user engagement required, and the urgency of action needed based on AI-generated information. These differences can generate varying interaction dynamics between the end-users and the AI-based DSSs and thus potentially distinct interactive needs in the three types of AI-based DSSs, as shown in Figure 1.

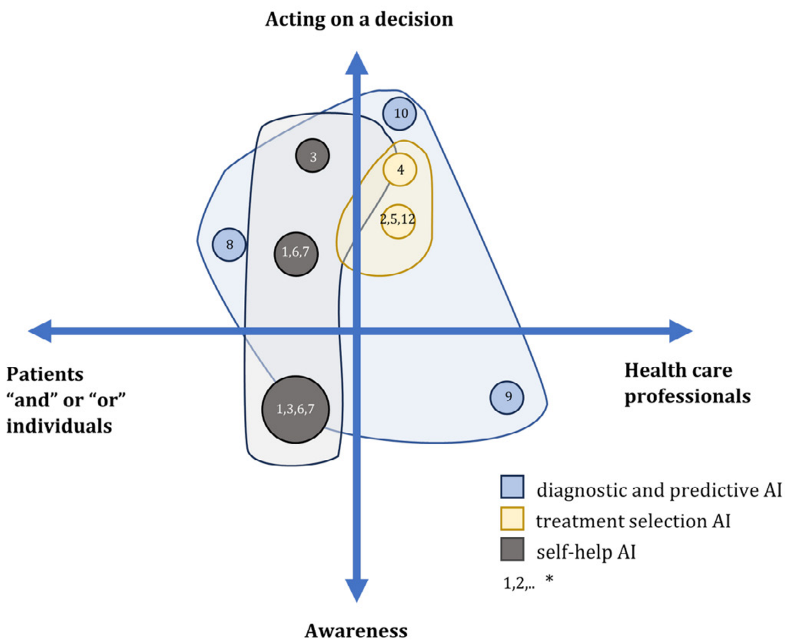

Figure 1. Mapping the decision-support utility of the artificial intelligence (AI) systems on two dimensions: (1) the extent of actionable output the AI system provides and (2) the types and variety of potential end-users using the AI system output.

* Indicates the studies included: (1) Dosovitsky et al (2020) ; (2) Benrimoh et al (2021); (3) Dimeff et al (2021); (4) Jacobs et al (2021); (5) Popescu et al (2021); (6) Prochaska et al (2021); (7) Prochaska et al (2021); (8) Deng et al (2022); (9) Garriga et al (2022); (10) Megerian et al (2022); and (12) Tanguay-Sela et al (2022).

Data flow and user's interaction with the AI-based DSSs

The varying structure of the three types of AI-based DSSs shows different potential advantages and challenges of use and implementation in mental health (Figure 6). For diagnostic and predictive AI, more data sources were used, and there was a lower degree of diversity of end-users directly engaged in using the output. For treatment selection AI, a smaller number of data sources was used but more diverse scenarios of end-users that may use the output. For conversational agents in self-help AI, different interfaces for output were used in which different end-users had different sequential interface interactions.

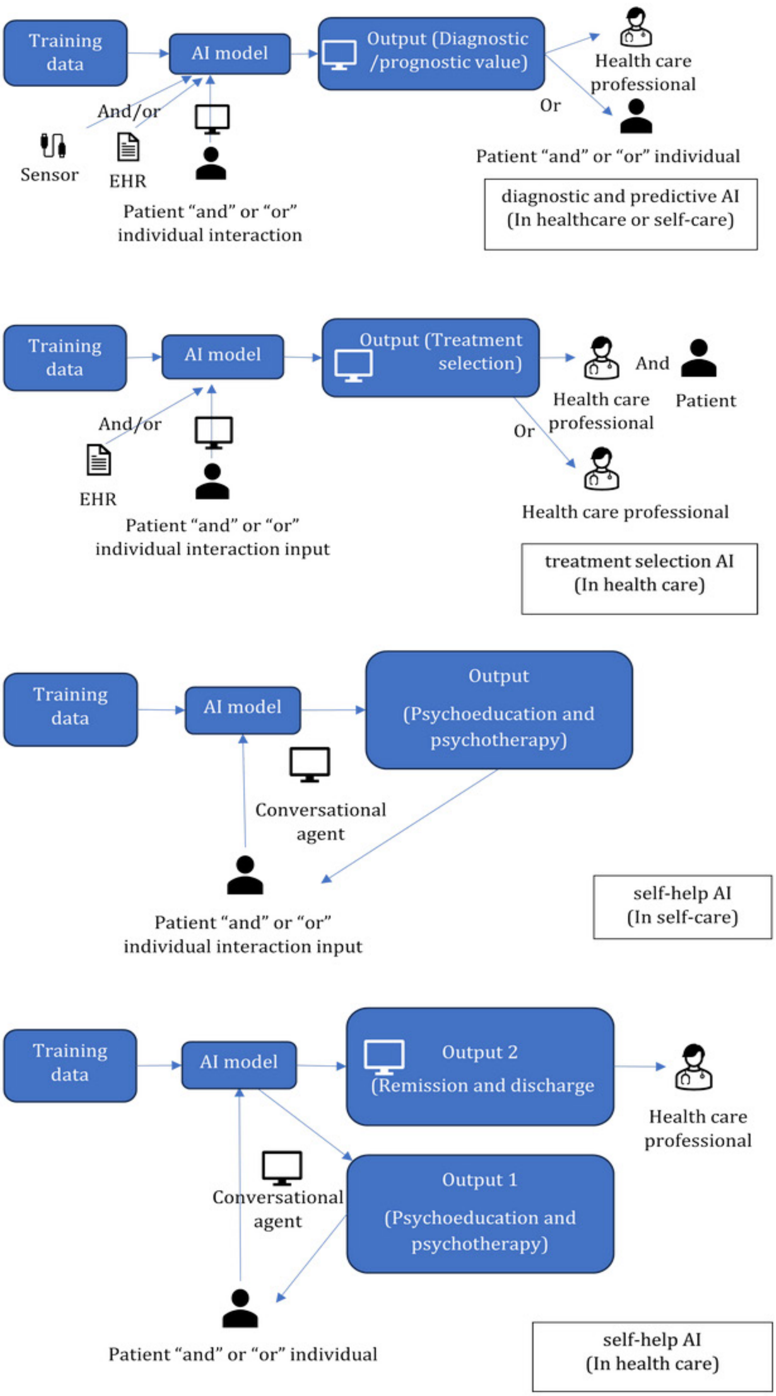

Figure 2. Illustration of the data and user flow journey of the three types of AI-based DSSs.

6.1.3 Evaluation of the implementation and use of the AI-based DSSs

The findings revealed a variation in how the studies evaluated AI-based DSSs concerning human, organization, and technology factors. These factors were more evenly represented in diagnostic and predictive AI, as well as treatment selection AI. In contrast, self-help AI exhibited a predominant focus on the human factor, highlighting implementation and usage challenges (Appendix B). The organizational factor was the least frequently assessed across all the types.

Diagnostic and predictive AI

The evaluation of diagnostic and predictive AI in mental health was found in three articles (Deng & Rattadilok, 2022; Garriga et al., 2022; Megerian et al., 2022), in which the authors primarily emphasized denser investigation regarding technology factor, specifically accuracy and ease of use, while less investigation was found related to human and organizational factors. The studies highlighted that data relevance and stakeholder inclusion are crucial for developing accurate AI, as outdated or missing data may negatively impact AI performance. For example, the caregiver's input was missing in one of the AI-based DSSs, which was referred to as important and would influence the AI functionality (Deng & Rattadilok, 2022). Ease of use was expressed as a positive aspect in the identified articles. However, some evidence from the articles showed that healthcare professional's lack of understanding of AI outputs influenced their decision to follow the AI decision negatively, and in one study the use of AI added to the workload by signaling cases in which the healthcare professional needed additional efforts to validate before acting on it, adding extra steps to their workflow (Garriga et al., 2022; Megerian et al., 2022). The facilitators for implementation found in the three studies included the need for appropriate training for healthcare professionals on AI accompanied by technical support, whereas barriers involved concerns about responsibility and increased workload.

Treatment selection AI

Four articles were identified that included the evaluation of treatment selection AI (Benrimoh et al., 2021; Jacobs et al., 2021; Popescu et al., 2021; Tanguay-Sela et al., 2022). In the human factor, elements such as duration of use, user knowledge, and perceived usefulness were found to potentially affect AI use and implementation. Healthcare professionals preferred interacting with the AI if the duration was five minutes or less (Benrimoh et al., 2021). The increase in ML familiarity was associated with reduced reliance on AI recommendations despite recognizing their utility (Jacobs et al., 2021). Healthcare professionals found AI-based DSSs useful for improving patient-clinician communication and may lead to enhancing the understanding of treatment options (Tanguay-Sela et al., 2022). Technological elements such as accuracy and trustworthiness were found in the identified articles. Trust was influenced by the relevance and understanding of AI features and the ability to understand the AI processing method by healthcare professionals (Tanguay-Sela et al., 2022). For the organization factor, AI-based DSSs impacted patient-clinician communication dynamics, with some healthcare professionals feeling it may hinder the interaction flow while others saw it as valuable for making decisions with the patients (Tanguay-Sela et al., 2022).

Self-help AI

The evaluation of self-help AI in mental health was found in four studies and the focus was predominantly on human factors such as duration of use, completion rates, frequency of use, acceptability, and user satisfaction (Dimeff et al., 2021; Dosovitsky et al., 2020; Prochaska, Vogel, Chieng, Baiocchi, et al., 2021; Prochaska, Vogel, Chieng, Kendra, et al., 2021). Two types were identified, the first type operates under healthcare supervision (Dimeff et al., 2021), and the second type is based on self-care remote help (Dosovitsky et al., 2020; Prochaska, Vogel, Chieng, Baiocchi, et al., 2021; Prochaska, Vogel, Chieng, Kendra, et al., 2021). Systems with healthcare supervision demonstrated more consistent use and better completion rates of psychoeducational materials compared to unguided conversational agents, which were inconsistent and influenced by the user's intrinsic motivation and engagement dynamics. Levels of satisfaction and perceived usefulness were generally high across the four studies, but acceptability varied based on factors such as the severity of mental health conditions and socio-economic status, including cultural background and education level (Prochaska, Vogel, Chieng, Baiocchi, et al., 2021). Technology elements such as ease of use and usefulness were perceived as being overall positive, while organizational factors were not investigated.

6.2 Study 2

6.2.1 Essential elements

This category explores needs and concerns tied to four of the nine SDM essential elements: 1) defining/explaining the problem, 2) patient values/preferences, 3) Healthcare professional knowledge/recommendations, and 4) arranging follow-up.

Defining/Explaining the problem

The healthcare professionals emphasized the potential for AI in assisting with the definition and explanation of mental health conditions, through early detection, condition monitoring, and suicide risk identification. They emphasized that AI-based tools could help identify patterns, enabling more holistic and needs-focused assessments rather than using rigid forms. By incorporating lifestyle factors, AI has the potential to improve triage accuracy and promote patient empowerment.

However, the participants raised concerns that AI may misinterpret language and non-verbal cues during assessment, potentially leading to misdiagnosis. They highlighted that young adults, in particular, may be more vulnerable to AI inaccuracies due to the rapid and dynamic changes in their lives. Other concerns were related to AI reliance potentially reducing the quality of human interactions, causing stigmatization, or reducing clinicians' autonomy if it was implemented in a non-inclusive method.

Patient values and preferences

The healthcare professionals emphasized the need for AI in evaluating the care process, particularly in understanding patient satisfaction, ensuring that treatment options align with patient values and preferences, and assessing patients' intrinsic motivation to engage in and adhere to their care plans. AI was reviewed as a valuable tool that can accommodate individual preferences, enabling young adults to access healthcare physically or remotely. It can also assist in tailoring interventions to better meet their specific needs.

Healthcare professional knowledge and recommendations

The healthcare professionals highlighted the need for AI to enhance their knowledge by providing effective treatment recommendations, particularly for complex multi-morbid cases. The needs expressed were focused on AI's ability to offer step-by-step recommendations that consider lifestyle and risks factors, as well as providing recommendations during triage to enable early recommendations and interventions. Concerns centered around the potential loss of clinical autonomy, trust issues in communicating AI-based recommendations to patients, and discrepancies between AI suggestions and real-world contexts. Participants also raised questions about accountability if AI-driven recommendations result in patient harm. Ensuring transparency and preserving human agency in decision-making were viewed as critical to maintaining trust.

Arranging follow-up

The participants emphasized their need for AI to help in arranging follow-ups in different phases in the patient trajectory. Its help was requested with prioritization and initial scheduling during triage, matching the patient's case with the most relevant unit of care. At the end of consultations, AI was seen as a tool that could assist in scheduling follow-ups by considering both the patient's and healthcare professionals' perspectives, thereby fostering a collaborative approach to care. The participants expressed a need for AI to support with assessing patient status and evaluating the necessity and time of the next follow-up based on patient's needs between sessions. Concerns included the risk of the AI misdirecting the patients, leading to potential waste of time, and reduction of trust in healthcare. In addition, an over-reliance on AI for scheduling was seen as potentially leading to problems such as disconnect from the human factor and possible lack of accessibility or acceptance to use the AI technology by some young adults with mental health problems.

6.2.2 Ideal elements

This category explores needs and concerns tied to three of the four ideal elements of SDM: 1) unbiased information, 2) presenting evidence, and 3) defined roles.

Unbiased information

The healthcare professionals highlighted the need for AI to support more objective and unbiased assessments, by providing visualized insights, helping to minimize subjective interpretations.

Presenting evidence

The participants viewed AI as a valuable tool for presenting evidence-based information, particularly in prevention and early intervention efforts. AI could serve as a foundation for decision making by providing scientifically grounded insights from complex data sources.

Defined roles

The healthcare professionals raised critical concerns about the ambiguity of responsibilities when using AI-derived predictions, particularly in defining who is accountable for acting on these predictions or communicating them for prevention purposes.

6.2.3 General elements

This category explores needs and concerns tied to eight of the ten SDM general elements: 1) flexibility and individualized approach, 2) information exchange, 3) involving at least two people, 4) mutual respect, 5) partnership, 6) patient education, 7) patient participation, and 8) process/stages.

Flexibility and individualized approach

The healthcare professionals expressed a need for AI to support more flexible care approaches, particularly within cognitive behavioral therapy (CBT) and psychoeducation programs. These interventions could be more adapted to young adults' varying levels of understanding and needs through personalized navigation. The participants also illustrated the need for more flexibility in the triage system incorporating dynamic and qualitative features into assessments, allowing for a more nuanced understanding of individual needs and improved decision-making.

However, they also expressed concerns that the intermediate role of AI might weaken the therapeutic alliance, reduce the quality of human interaction, reinforce specific stigmas, or jeopardize patient safety.

Information exchange

The participants expressed that AI could be a valuable tool in facilitating the exchange of patients' expectations, preferences and worries, enabling more meaningful and personalized communication between a healthcare professional and the patient. They also expressed the need for AI to address both medical and personal information in order to exchange and identify the most relevant information from both healthcare professionals and patients. However, concerns emerged around data privacy and poor AI implementation systems that might increase stress or create a burden on workflows.

Involving at least two people

The healthcare professionals viewed AI as a potential enabler of non-physical access to care, ensuring that two-way interaction remains possible even when patients cannot or do not want to attend in person.

Mutual respect

The healthcare professionals emphasized the need for ensuring that AI adopts a non-stigmatizing approach when supporting young adults, and in addition for it to be applied with respect to the healthcare professional's expertise.

Partnership

The participants illustrated that AI could indirectly help the partnership by freeing more time for human interaction and providing relevant information that can make the focus be directed to human interaction. However, societal and institutional barriers, in relation to a lack of reaching out to young adults and integrating their lifestyle perspectives into the AI-based DSSs, could hinder these efforts. In addition, the potential exclusion of healthcare professionals or patients from the AI development process was seen as an integral barrier to achieving systems that are built on collaborative insights.

Patient participation

The participants highlighted that AI could improve accessibility and encourage more active involvement in care by identifying those who require greater participation and providing digital avenues for them to engage with the support of AI. However, they also expressed concerns if AI responses are not inclusive, leaving young adults feeling unseen or not heard, and thus maybe reducing their willingness to participate.

Patient education

The participants perceived AI as a potentially valuable tool to identify, address, and support navigating young adults' education needs and supporting them with relevant psychoeducational materials.

Process and stages

The participants recognized AI as a potential solution to bridge the gap between primary and specialized care, helping the patient to navigate through the healthcare process. AI could predict and clarify the next steps in the care process, reducing inefficiencies, and ensuring smoother transitions for young adults as they move through different stages of care. This could improve overall care coordination and make the healthcare process more seamless and accessible for patients.

7 Discussion

7.1 Principal findings

The findings presented in this thesis identified a range of potential roles for AI as well as several challenges when implementing an AI-based DSSs with a focus on SDM. The types of AI-based DSSs in mental healthcare that emerged in the scoping review in Study 1 could be categorized into three different utility types: diagnostic and predictive AI, treatment selection AI, and self-help AI. A variety of dataflows, end-user interaction dynamics, challenges and enablers for implementation and use for these types were found that can indicate different needs to be adjusted to when AI is implemented in care workflows. The healthcare professionals in the interviews in Study 2 emphasized the need to facilitate early detection of mental health problems and connect it with young adults' lifestyles, provide comprehensive assessments that combine both personal and medical young adults' perspectives, and deliver tailored treatment recommendations. However, concerns were also highlighted regarding the limitations in the accuracy of AI in reading non-verbal cues, the possibility of diminishing clinician autonomy, and potentially undermining trust and the therapeutic relationship when the human factor is undermined by AI's newly implemented utilities.

Learnings to inform AI-based DSSs design

The dataflow and user interaction journeys of the AI-based DSSs described in Study 1, together with the findings of Study 2, revealed several opportunities to integrate SDM into these systems. According to the healthcare professionals in Study 2, SDM can potentially be integrated into AI input interfaces by ensuring that the data submitted not only includes medical information but also personal insights from the patient's perspective. AI can support the integration of data from various sources such as electronic health records (EHR), which can improve the healthcare professional's ability in diagnostics, delivery of care, and various decision support (Ye et al., 2024). However, this integration and exchange of information comes with several considerations that need to be addressed during the implementation, including personal information privacy concerns, organizational barriers, and technical adjustment (Eden et al., 2016; Lee et al., 2022).

A key aspect of integrating young adult's needs and preferences in AI-based DSSs is the use of flexible triage forms that allow them to articulate their concerns in their own words, ensuring that their perspectives are accurately captured. This approach has the potential to empower SDM as a collaborative process where healthcare professionals and patients work together to make informed decisions, balancing clinical expertise with individual preferences and values (Makoul & Clayman, 2006). The findings in Study 2 showed that there is a strong desire for AI to support one or more elements of the SDM process described by Makoul and Clayman (2006). This can be translated to potentially benefit supporting specific SDM phases in the context of practical SDM models. For example, assisting the SDM three-talk model that consists of three key stages: choice talk (introducing available options), option talk (discussing alternatives), and decision talk (helping patients make an informed choice) (Elwyn et al., 2012). Based on the findings of Study 2, AI-based DSSs can be designed to support each of these steps by accurately capturing patients' perspectives, facilitating information exchange, presenting unbiased, evidence-based information, and tailoring recommendations to individual patient data. However, there is a lack of research that explores how specialized AI-based DSSs can be designed and implemented to support SDM models in practice. It has been emphasized that involving diverse stakeholders, particularly patients, in the design phase is crucial for supporting the fostering of early partnerships in AI development. Research highlights that this collaborative approach not only helps achieve the desired AI outcomes but also ensures that the system is tailored to align with the needs, preferences, and expectations of its users (Gu et al., 2024; Hogg et al., 2023).

Integrating AI-based DSSs in mental health workflows to enhance SDM

The findings from Studies 1 and 2 demonstrate that diverse AI applications ranging from diagnostic and predictive AI systems to treatment selection AI systems and self-help AI systems may have different implications for integration into clinical and self-help workflows for SDM. Diagnostic and predictive AI-based DSSs may aid in the early identification and monitoring of conditions, thereby supporting clearer problem definition and potentially empowering patients with the relevant information (Aslani, 2013). However, the poor implementation of these AI-based DSSs can end with such information creating more harm than benefits; for example, it can create anxiety and stress for young adults if the information is not presented properly as emphasized by the participants in Study 2, or leading to time-consuming decision paralysis when a black-box information existed in the predictive AI output. This can happen when the healthcare professional does not have a clear interpretation of how the AI has reached the predictive conclusion (Triberti et al., 2020).

Treatment selection AI systems have the potential to support aligning clinical recommendations with patient values, fostering improved communication and collaborative decision-making (Tanguay-Sela et al., 2022). However, challenges may persist when integrating these support systems into clinical workflows. Healthcare professionals in Study 2 illustrated the need for AI support to incorporate patients' values and preferences in the AI recommendations when providing relevant intervention options, which was neglected in the treatment selection AI systems in Study 1. Akhai (2023) highlighted a critical aspect of AI-based recommendations, which is ensuring the transparency and interpretability of the AI models to avoid black boxes, which is consistent with the findings in Study 2 illustrating that healthcare professionals need clarity and transparency about the AI-used model to adopt the AI output. When the underlying logic of an AI system remains opaque, both clinicians and patients may struggle to trust its outputs, potentially hindering the collaborative approach of SDM (Quinn et al., 2022).

In Study 1 scoping review, articles examining supervised self-help AI-based DSSs delivered via conversational agents in healthcare settings have shown stable user engagement and completion rates of psychoeducational materials. These findings align with previous research that highlights the efficacy of guided digital interventions in enhancing patient outcomes, however, it was noted that these effects are short-lived, needing long-term engagement, and a goal-setting content to achieve effectiveness in dealing with mental health problems (Opie et al., 2024). Self-help AI systems designed for unsupervised self-care face variety of challenges, such as inconsistent user engagement and misinterpretation of non-verbal cues processed by the AI, and can potentially weaken the therapeutic alliance if poorly implemented as illustrated in Studies 1 and 2. This requires more research that could explore how AI-driven self-help conversational agents can balance autonomy with personalized guidance, and how to overcome challenges such as user adherence and interpretation of non-verbal cues, which is consistent with several studies confirming this need (Foran et al., 2024; Leung et al., 2022; Park et al., 2024).

The integration of AI-based DSSs into mental health workflows holds the potential for advancing SDM practices. However, the findings from Study 1 indicate that AI-based DSSs in mental health is still in the pre-implementation stage in practice. A total of only 12 studies were identified that evaluated the use of AI-based DSSs and their potential impact on clinical workflows. To fully realize the benefits of AI-based DSSs in mental health, it is essential to evaluate the implementation of these tools into clinical workflows through thoughtful planning and active stakeholder engagement (Nair et al., 2024). This can help address organizational AI-SDM barriers to help refine AI outputs which is crucial to meet the healthcare professionals' and patients' needs for autonomy and trust (Shay & Lafata, 2015).

Empowering participation through AI-based DSSs with integrated SDM

It can be suggested from the findings in Studies 1 and 2 that the use and implementation of AI-based DSSs in mental healthcare, with a focus on SDM, can influence participation and empowerment depending on the quality of design, implementation, and sustainable use. The findings from Study 2 highlight the potential of AI-based DSSs to improve accessibility and encourage young adults to become more engaged in their healthcare. These systems can provide opportunities for education, increase health literacy, and empower patients by enhancing their understanding of their health and care options. However, concerns were also raised in Study 2 that if the AI responses are not inclusive or empathetic, young adults might feel unheard or overlooked, which could diminish their ability to participate in decision-making. In relation to these findings, the concept of the locus of empowerment, according to the three dimensions: individual, organizational, and community-based, as presented by (Wiggins, 2012), provides a useful framework for understanding the potential impacts of AI-based DSSs. The explored AI-based DSSs in this thesis touched on potential empowerment outcomes of SDM integration in these systems on individual and organizational aspects. For example, in Study 1, AI support is placed on several healthcare workflows intermediating between the healthcare professional and the patient, showing the capacity of providing psychoeducation support to the patient to potentially empower the patient's SDM participation. The participants in Study 2 emphasized the importance of empowering young adults to articulate their perceived problems and providing an understanding connected to their lifestyle events. While interaction with AI-based DSSs has the potential to influence individual empowerment, it is the responsibility of healthcare providers to design these systems in a way that can create interaction dynamics that lead to empowerment outcomes. Future efforts to measure the empowerment outcomes of participation in AI-based DSSs, particularly when SDM is incorporated is thus crucial as it could pave the way for developing and using AI-based DSSs in supporting sustainable human-AI collaborative approach (Thieme et al., 2023).

7.2 Methodological considerations

Study 1

Several methodological considerations should be acknowledged in the scoping review. First, the literature searches were conducted using five databases selected based on the study's aim and research domain. While this approach with the guidance of Tricco et al. (2018) aimed to ensure coverage of the most relevant scientific search sources, the use of exclusion of other databases can result in potentially limiting the identified articles to these databases. The literature search strategy was developed through discussions within the research team and with librarian assistance to align with the study's objectives. However, the interdisciplinary nature of the study, including healthcare, implementation science, and AI technology, means that the literature employs diverse terminology, which may have influenced the identification and inclusion of relevant studies. Variability in terminology across the fields could have resulted in the exclusion of potentially relevant studies that used alternative keywords other than those used in the searches.

Second, the inclusion criteria used in the screening process required AI systems to have a technology readiness level (TRL) of 6 or higher (Mankins, 1995), which intended to concentrate the focus of the review on AI-based DSSs close to implementation in care settings. While these criteria ensured relevance to real-world use, they also limited the scope by excluding studies on earlier stages such as AI model development or AI performance studies. Consequently, this review does not capture insights into emerging AI technologies that remain in the technical performance or proof-of-concept phase. However, using this criterion may hold significant implications for implementation efforts for mental health applications in the future.

Third, study selection and data extraction were conducted independently by two researchers to enhance reliability and minimize bias (Peters et al., 2015). However, assessing SDM in the context of AI-based DSSs presented challenges, as most studies did not explicitly report on the interaction dynamics between healthcare professionals, patients, and AI systems within a collaborative decision-making framework. This lack of detailed reporting on SDM may reflect limitations in the ability to evaluate how AI can facilitate or influence SDM in mental health care.

Finally, the limited number of studies in this scoping review investigating the use and implementation of AI-based DSSs in different care settings constrains the ability to draw generalizable conclusions regarding the long-term effectiveness and scalability of these systems in mental health. This limitation reflects the generalizability challenge inherited in the scoping review study design as noted by Arksey and O'Malley (2005).

Study 2

The study design and findings pose several methodological strengths and limitations. First, semi-structured, open-ended interviews were employed to capture the healthcare professionals' perspectives on AI's potential in supporting decision-making. This interview format enabled themes related to SDM needs and concerns to emerge in a natural flow, thereby reducing the risk of bias that might occur with more directive questions. Such an approach is particularly pertinent given the evidence that many healthcare professionals have limited formal training or theoretical knowledge regarding SDM practices (Mathijssen et al., 2020; Schoon, 2022). However, because the interview guide did not explicitly target SDM, the study was less able to probe specific, practical SDM needs that AI might address directly, and avoiding the high level of interpretation to maintain trustworthiness of this research (Graneheim et al., 2017). Despite this limitation, the interviews resulted in several perspectives reflecting on the SDM integrative model by Makoul and Clayman (2006), and detailed insights from the participants' perceptions, experiences, and concerns. These findings provide a valuable foundation for future research aimed at exploring the integration, implementation, and design of AI systems to facilitate SDM in mental healthcare settings.

Second, the study design exhibits strength for the inclusion of the diverse backgrounds of mental healthcare professionals, which helped provide a broader perspective within the care provision domain. However, a more comprehensive understanding of SDM integration would benefit from including the perspectives of other stakeholders, such as young adults. Future studies might benefit from the incorporation of visualizations or prototypes that can help create a shared understanding of AI, SDM, and the implementation processes among all stakeholders with diverse backgrounds in order to reach better meaningful research outcomes.

The third consideration relates to the interview administration and subsequent transcription process. The data were collected in Swedish by three experienced researchers and, after translation, were analyzed by the primary investigator in English. This procedure may have resulted in the loss of some linguistic nuance. To mitigate this potential limitation, the primary investigator conducted the analysis individually, with iterative discussions and validation within an interdisciplinary research group to ensure a robust and unbiased interpretation of the data, and with the assistance of native Swedish-speaking professional proofreader for the data included in the manuscript (Fryer, 2019).

7.3 Implications for practice and future research

The integration of AI-based DSSs into mental healthcare services provides promising avenues for enhancing SDM and person-centered care. In practice, the findings highlight the need to use AI as a supportive tool rather than a replacement for clinical expertise, thereby preserving both autonomy and the essential human factor that was perceived as crucially important in Study 2. Healthcare organizations need to equip staff with training programs before fully implementing AI-based DSSs in order to adapt to this ongoing change (Nair et al., 2024). These programs suggested focusing on providing clarity in relation to interpreting and integrating AI-based insights in workflows, ensuring that the users are well informed about how the AI functions in the context of use (Schuur et al., 2021). Moreover, the implementation of AI in diverse settings, including healthcare and self-help platforms requires careful consideration of user engagement challenges and ethical consideration, including transparency to apply SDM (McDougall, 2019; Triberti et al., 2020). The findings from this thesis suggest that fostering a collaborative development approach involving both healthcare professionals and young adults can be beneficial. Mental health services can use this collaborative approach to plan for AI outputs to be supportive of nuanced, evidence-based mental health outcomes and more effective SDM processes (Yoo et al., 2024).

The findings in Study 2, interpreted through the integrative model of Makoul and Clayman (2006), indicated the importance of integrating the SDM approach into the design and implementation of AI-based DSSs. However, the scoping review in Study 1 did not reveal any current empirical evidence investigating the potential use of AI for SDM support in practice. This is a key gap that underscores the need for future empirical research, particularly in mental health applications, that supports the understanding of how to implement AI-based DSSs with the incorporation of the SDM approach.

Potential implementation challenges of AI-based DSSs in mental healthcare were identified in both Studies 1 and 2. However, no studies were found that examined a fully implemented AI-based DSSs in this field, and the healthcare professionals did not report any firsthand experiences of using such a system. This highlights a significant gap in research on the real-world application of AI in mental healthcare, emphasizing the need for further studies to address this limitation.

When exploring the potential integration of SDM in AI, it appears that existing models and theories of SDM may require updates to reflect the novelty of AI-based support. As AI continues advancing, imitating human cognitive abilities and executive functioning, current SDM models need to adapt the new interaction dynamics such as AI-patient SDM or AI-healthcare professional-patient SDM. This relational evolution could extend the SDM multi-consultant model (Moleman et al., 2021) in which AI can potentially participate as one of the consultants in the SDM process. This requires further studies to explore how to move to this conceptual evolution.

8 Conclusions

In conclusion, this thesis highlights the potential of AI-based DSSs to enhance SDM and person-centred care in mental healthcare. However, research in this area, particularly regarding the role of AI in promoting SDM, remains in its early stages. The findings indicate that while AI can support various elements of the SDM process, a holistic approach is essential for its successful integration into AI-based DSSs. Therefore, further empirical studies are needed to assess the impact of these systems on decision-making and to address the existing gaps in SDM research.

The two studies presented in the thesis illustrate that implementing AI-based DSSs for SDM support in mental health is a complex process influenced by technological, human, and organizational factors that shape barriers and facilitators for sustainable use. These systems illustrated the potential in supporting variation of care tasks such as mental health evaluation for diagnosis and prevention, treatment, triage, psychoeducation, and self-help, with particular potential for SDM support. However, while AI systems used for mental health assessment showed primarily technology-related investigations in literature, human and organizational investigations were overlooked. Missing the investigations of human interaction may lead to negative consequences; healthcare professionals illustrated their concerns that missing verbal information and human alliance can affect the accuracy and trust of these systems when used by the end-users. AI-based DSSs assisting treatment has several potential roles in supporting the decision-making process such as suggesting recommendations or identifying the most relevant interventions. These systems demonstrated the potential need for additional efforts for integrating an SDM approach due to the potential need for interactions between healthcare professionals and young adults to discuss the AI output, and to effectively bridge the gap between AI outputs and both patient-specific lifestyle factors and clinical expertise to maintain individualized and autonomous decision support. Self-help conversational agents and triage supported by AI may come hand in hand as a transitional process coordinating between remote self-care and professional healthcare, which can operate with or without healthcare provision, showing different challenges such as patient engagement with remote self-help and the proper direction to the appropriate mental healthcare unit matching the needs of the young adults. Addressing these challenges may require innovative approaches for pave the way for seamless transition between self-care and professional help.

Therefore, the successful implementation of AI-based DSSs in healthcare hinges on a balanced strategy that leverages advanced technological capabilities while rigorously addressing the human factors that are essential for sustainable, person-centred care and SDM practices.

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Appendices

Appendix A. Shared decision-making (SDM) elements used in the deductive analysis adapted from Makoul and Clayman (2006).

Essential elements	Ideal elements	General elements
Define/explain problem	Unbiased information	Deliberation/negotiation
Present options	Define roles	Flexibility/individualized approach
Discuss pros/cons (benefits/risks/costs)	Present evidence	Information exchange
Patient values/preferences	Mutual agreement	Involves at least two people
Discuss patient ability/self-efficacy		Middle ground
αHealthcare professional knowledge/recommendations		Mutual respect
Check/clarify understanding		Partnership
Make or explicitly defer decision		Patient education
Arrange follow-up		Patient participation
		Process/stages

[α]: In Makoul and Clayman (2006), the element originally labeled “Doctor Knowledge/Recommendations” has been adjusted to “Healthcare Professional Knowledge/Recommendations” to reflect that SDM can involve a multi-consultation model, including “non-doctor” healthcare professionals such as nurses, social workers, and others, in addition to doctors.

Appendix B. Summary of the human, organization, and technology-fit (HOT-fit) elements found in the 3 types of artificial intelligence (AI) systems and key findings of potential challenges and enablers of use and implementation.

HOT-fit elements	AI system type	Key findings,challenges (–), and enablers (+)
Human		
Amount and duration	Diagnostic and predictive, treatment selection, and self-help	(–) Prominent inconsistent duration of use found in self-help AI in self-care settings
Motivation to use	Self-help	(–) Potential lack of motivation for long-term of use without external support
Acceptance	Self-help	Different acceptance according to user's socioeconomic status
Recurring use	Self-help	(–) Unstable recurring use can disturb the evaluation of self-care conversational agent's effectiveness
Expectations and belief	Self-help	Most users expressed that the conversational agent met some of their goals or needs, only few users expressed that it met most or all their needs
Resistance and reluctance	Self-help	(–) Potential onboarding resistance and discontinuation after the first or second step in self-care settings
Percentage used	Treatment selection and self-help	(–) Low completion rates in self-help AI in self-care settings
Voluntaries of use	Self-help	Users are more likely to engage when initiated by the conversational agent
Knowledge and expertise	Treatment selection	(+) Knowledge about the AI model can potentially improve the ability to explain the AI output (–) Previous knowledge about the AI in general may reduce the trust
Overall satisfaction	Diagnostic and predictive and self-help	(+) Overall satisfaction was relatively high in relation to the amount of help the end users got from the system, the consistency of the system, and if they would use it again or recommend it for others
Perceived usefulness	Diagnostic and predictive, treatment selection, and self-help	(+) When evaluated most of participants perceived that the AI systems can successfully assist them
Satisfaction with specific functions	Treatment selection and self-help	Self-help AI satisfaction varied according to the self-help topic Treatment selection AI satisfaction was related to information the AI provided and can help with the communication with the patient
Decision making satisfaction	Treatment selection	(–) When evaluated only 60% expressed that the model is somehow satisfactory to support treatment decisions
Organization		
Communication	Treatment selection	(+) Potential participation in improving the communication of options or decisions
Clinical process	Diagnostic and predictive and treatment selection	(+) Positive responses on the ability to transform current clinical practice (–) Can lead to increase of workload by introducing additional steps into their practice
Localization	Diagnostic and predictive	Potential change of AI performance when used in different environments in relation to stability
Technology		
Ease of use	Diagnostic and predictive and self-help	(–) Potential difficulty requiring the need for technical support during the use of AI system
Technical support	Diagnostic and predictive	(–) Expressed need for assistance to get introduced to the system to be able to start using it

Usefulness of system features and functions	Diagnostic and predictive, treatment selection, and self-help	(+) Providing options, identification of cases and prioritization support features were found useful by participants of the different systems (–) The need for time to onboard to use the different features were expressed
Data accuracy	Diagnostic and predictive	(–) Outdated data and misrepresentation of data can lead to lower AI model accuracy
Trustworthiness	Treatment selection	(–) Affected by the end user’s knowledge, the AI processing methods, and onboarding use
Explainability	Diagnostic and predictive and treatment selection	(–) Lack of explainability can affect trust negatively
Usefulness	Diagnostic and predictive, treatment selection, and self-help	(–) Potential misalignment between what the end users found useful compared with AI intended purpose of use
Relevance	Diagnostic and predictive	(+) Most end users found the self-help service relevant to their wants.
Reliability	Treatment selection	(–) Potential misalignment of AI processing method compared with the health care method
Accuracy	Treatment selection	Potentially affected by the environment used in, and health care professional’s confidence in their decision.
Empathy	Treatment selection and self-help	(–) Potential skepticism by health care professionals “AI interprets data, but people are not data”

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Hassan holds a master's degree in public health with health economics. He is a dentist, and has diverse experience working with digital projects in eHealth, gamification, and eLearning. He began his academic journey at Halmstad University in Health & Lifestyle in 2022 with a focus on the use and implementation of artificial intelligence (AI) in decision support in mental health particularly with an eye on the integration of shared decision-making between healthcare professionals and young adults in these systems.

Drawing from his work and academic journey, he advocates for a crucial shift in perspective; as AI evolves and redefines the human perception of intelligence as a concept exceeding human abilities, wisdom needs to be conceptualized and adopted as a pillar of future human capital to ensure a meaningful and adaptive response to this transformation

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