Supporting sensemaking of data in healthcare: A multi-method approach

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Gemza Ademaj

DOCTORAL DISSERTATION

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Drawing on a multi-method approach comprising five research papers, this dissertation develops theoretically informed and practically oriented support for sensemaking of data across three distinct functional roles: data as a tool, data as a practice, and data as algorithmic intelligence. Each role presents unique sensemaking challenges that require tailored forms of support.

The contributions of this thesis are threefold. First, it develops an integrated framework that delineates two essential dimensions of sensemaking support: interpretive support, which makes visible how data becomes meaningful through interaction, collaboration, and tool design and contextual fit support, which ensures that meaning aligns with the situated demands of clinical practice, disease-specific reasoning, and professional roles. Second, it contributes a multi-method approach that develops conceptual, processual, and design contributions tailored to each form of sensemaking support. Third, it advances the design of computational artifacts by demonstrating how tools can be designed to support sensemaking of complex data in the context of mental health assessments. By exploring and offering support that is both exploratory and nuanced, the thesis advances healthcare Information Systems research on sensemaking of data, data use, healthcare technologies, and the collaborations between healthcare practitioners and artificial intelligence.

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MADE IN SWEDEN

To my parents

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Abbreviations

AI	Artificial Intelligence
DSR	Design Science Research
IT	Information Technology
IS	Information Systems

Abstract

In healthcare, the ability to make sense of data is crucial for informed and responsible decision-making. However, the ongoing digitalization of healthcare and its reliance on heterogeneous forms of data has made sensemaking increasingly complex. Data is generated, presented, and used through a variety of tools, practices, and algorithmic systems, and its meaning demands careful and context-sensitive interpretation that accounts for disease context, patient characteristics, and clinical workflows. This thesis addresses the research question: *How to support the sensemaking of data in healthcare?*

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By exploring and offering support that is both exploratory and nuanced, the thesis advances healthcare Information Systems research on sensemaking of data, data use, healthcare technologies, and the collaborations between healthcare practitioners and artificial intelligence.

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This PhD journey has been as much about personal growth as it has been about academic discovery. I began this path with a strong technical background, grounded in data analysis and visualization ways of thinking. Along the way, this research pushed me beyond those foundations and exposed me to qualitative research, an approach that opened up new ways of thinking. Learning to navigate both worlds was challenging, but I feel very lucky to have been surrounded by amazing people who shaped this journey, guided me and pushed me to a better version of myself.

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List of Papers

This dissertation is based on the research described in the following appended papers. In the text of my dissertation, I refer to them with their respective numbers.

Paper I

Ademaj, G., Chowdhury, A., Sarker, S., & Keller, C. (2025). The role of narrative responsibility within Hybrid Intelligence. European Conference of Information Systems (ECIS), Amman, Jordan, 2025.

Paper II

Koukouvinou, P., Ademaj, G., Sarker, S., & Holmström, J. (2023). Ghost in the Machine: Theorizing data knowledge in the Age of Intelligent Technologies. International Conference of Information Systems (ICIS), Hyderabad, India, 2023.

Paper III

Ademaj, G, Zhang, X, Abbasi, A, Sarker, S, Sarker, S. (2025). Designing Support for Sensemaking in Multimodal, Multi-model Mental Health Assessments. International Conference of Information Systems (ICIS).

Paper IV

Ademaj, G, Zhang, X, Cai J., Sarker, S, Sarker, S. Abbasi, A. Sensemaking in Multimodal, Multi-model Environments: Designing Support for Remote Mental Health Assessments (Manuscript for International Journal Submission)

Paper V

Ademaj, G, Sarker, S, Sarker, S, Abbasi, A. Collaborative sensemaking of data in precision public health: A phronesis process model (Manuscript for International Journal Submission)

Introduction

In healthcare, the ability to make sense of data is crucial for informed and responsible decision-making (Maitlis et al. 2013). Sensemaking is understood as an interpretive process through which individuals and groups construct meaning from surrounding signals to inform their decisions (Abbasi et al. 2018; Kitchens et al. 2024a; Maitlis 2005; Vlaar et al. 2008; Weick 1993, 1995). This process has long been recognized as essential in uncertain and ambiguous settings (Maitlis 2005; Weick 1993). However, the ongoing digitalization of healthcare and its reliance on heterogeneous forms of data has made sensemaking more complex. The challenge is no longer simply having access to more data (Dalal and Pauleen 2019), but of making sense of it in ways that are situated, reflective, and clinically meaningful (Calvard 2016; Jones 2019; Xu et al. 2024). More specifically, sensemaking of data is a very sensitive process because the meaning derived from this process, and the decisions it supports, can vary significantly depending on which data receives attention (Kay 2022; Klein et al. 2007), how it is interpreted (Klein et al. 2007), for what purpose, by whom, and under what disease contexts (Calvard 2016; Lycett 2013).

In healthcare settings, data are generated, reframed, and interpreted through various tools, systems, and human actors, often under conditions of time pressure and clinical uncertainty (Baird et al. 2025; Bardhan et al. 2025; Jones 2019; Lebovitz et al. 2021; Maitlis et al. 2013; Pieper and Gleasure n.d.; Zon et al. 2023). Sometimes data appears as dashboards, reports, and decision-support tools (Abbasi et al. 2016; Khoury et al. 2019; Steen et al. 2017), sometimes it is enacted through everyday clinical routines and collaborative work (Elten et al. 2022; Gilson et al. 2021; Pieper and Gleasure n.d.) and sometimes it appears as algorithmic outputs such as risk scores or predictions (Lebovitz et al. 2021; Mao et al. 2025; Trocin et al. 2023). In such settings, data rarely "speaks for itself" (Calvard, 2016). Instead, it demands careful and context-sensitive sensemaking (Gagnon et al., 2025; Maitlis et al., 2013; Pieper & Gleasure, 2025; Zon et al., 2023) based on disease context, patient characteristics, and the way it is used in the clinical setting (Jiang et al., 2022;

Khoury et al., 2018; Pieper & Gleasure, 2025). Recent Information Systems (IS) research therefore calls for more human-centric perspectives that account for the multiple ways in which digital technologies, data, and Artificial Intelligence (AI) shape healthcare work, relationships, and decision-making (Bardhan et al., 2025). Importantly, how data appears deeply influences the nature of sensemaking.

Drawing from the conceptual frameworks of technology proposed by Orlikowski and Iacono (2001) and further extended by Xu et al. (2024), this thesis distinguishes between three functional roles of data based on what data does: data as a tool, data as a practice, and data as algorithmic intelligence. Each role presents distinct challenges for sensemaking and requires tailored forms of support. First, when data functions as a tool, it frames what becomes visible, comparable, or salient, meaning that sensemaking depends on how information is represented and connected within the designed artifacts (Lycett, 2013). The primary challenge of sensemaking in this context revolves around the design and interpretive use of engineered artifacts (Xu et al., 2024), meaning how well the tools that facilitate interpretation of data enable healthcare practitioners to perceive, interpret, and contextualize the data (Berente et al. 2021; Keim et al. 2008; Lycett 2013; Pirolli and Card 2005; Streeb et al. 2021a). Second, when data functions as a practice, it becomes meaningful through collective and iterative use across different roles, practices, and systems (Xu et al., 2024). The sensemaking challenges here arise from the need for coordination and shared meaning-making among diverse healthcare experts, pointing to the importance of collaborative aspects of sensemaking (Aaltonen et al. 2023; Jones 2019). Third, when data functions as algorithmic intelligence, it actively processes data and generates predictions, classifications, or recommendations, while both shaping and challenging the sensemaking process (Xu et al., 2024). While research shows that machine learning (ML) can effectively identify patterns and produce predictions (Jiang et al. 2024; Khoury et al. 2018), these outputs often create a misleading sense of objectivity due to their high accuracy (Lebovitz et al., 2021). Moreover, they may remain weakly aligned with clinical reasoning and patient-specific context, making them difficult to interpret or act upon safely (Lebovitz et al., 2021; Khoury et al., 2018).

Across these different ways in which data participates in healthcare work, sensemaking involves more than having access to data (Klein et al. 2006). It requires judgment, prioritization, and contextual alignment (Calvard 2016; Maitlis et al. 2013). Even technically accurate data can mislead if it is presented or interpreted without proper contextualization or attention to the nuances of the specific situation (Gagnon et al. 2025; Xu et al. 2024). The problem is that data often contain multiple, potentially competing signals that can be interpreted differently by different actors (Lycett, 2013). As Kay (2022) argues, such situations are intrinsically ambiguous as the same data can support different, equally plausible interpretations depending on what aspects are foregrounded. In healthcare, this means that misalignment and inconsistency can emerge even when data are accurate, because the challenge lies not in the data itself but in how it is made meaningful in context. (Kay 2022). A heart rate of 160 BPM, for example, could indicate fitness or fatal risk, depending on the patient, time of record, and the tool showing it (Zon et al., 2023 The risks of such misalignment are particularly high in healthcare, where mistakes can have serious consequences (Bardhan et al. 2025; Lebovitz et al. 2021). The challenge of sensemaking of data became especially visible during the COVID-19 pandemic. Despite an overwhelming volume of data, many decisions lacked the necessary contextual nuance (Kitchens et al., 2024), often failing to account for local conditions or the needs of vulnerable populations (WHO, n.d.), Hub for Pandemic and Epidemic Intelligence. This illustrates a broader issue that supporting sensemaking of data in healthcare, is not only about increasing data availability or promoting insight generation but about supporting the sensemaking process. This means understanding how data is made sense of, by whom, through which systems, and for what specific purposes (Kay 2022; Lycett 2013).

While IS research has contributed significantly to understanding data use, digital transformation, and analytics, it has paid limited attention to the practical and theoretical support of sensemaking, particularly in sensitive and contextually demanding environments like healthcare (Aaltonen et al., 2021; Aaltonen & Penttinen, 2021; Baird et al., 2025; Jones, 2019; Mikalsen et al., 2021; D. Xu et al., 2024). As data increasingly takes on diverse forms being used as tools, enacted in practice, or shaped by ML algorithms (Xu et al., 2024), it becomes clear that no single form of support can address all sensemaking challenges (Baird et al., 2025). From this perspective, it becomes clear why healthcare problems in IS are often described as "either multifaceted, localized, or conditional, and the identification of solutions often needs to be both exploratory and nuanced, where one solution is often not sufficient (Baird et al., 2025, p.578). A differentiated, multi-perspective approach is therefore needed.

Responding to recent calls in healthcare IS research that emphasize the complex and multifaceted nature of healthcare context (Baird et al., 2025), this thesis aims to develop and provide multi-perspective support for the sensemaking of data in healthcare. The purpose of the thesis is to provide theoretically informed and practically oriented support for sensemaking of data across various roles, specifically, as tool, practice, and algorithm in healthcare. To guide this research, the thesis investigates the following research question:

How to support the sensemaking of data in healthcare?

To address this question and fulfill the aim and purpose, the thesis first identifies the unique sensemaking challenges associated with each of the data roles: tool, practice, and algorithmic intelligence. It then examines the different forms of support needed for sensemaking across these roles. Finally, based on this, the thesis develops conceptual, processual, and design-oriented contributions that support healthcare practitioners in making sense of complex healthcare data.

Grounded in five research papers and a multimethod approach, this thesis offers a multi-perspective view of, and support for, sensemaking of data in healthcare in ways that are theoretically grounded and practically oriented. In the next section, I present the thesis research approach.

Research Approach and Contributions

The thesis is based on a doctoral research project comprising five papers, each reported in an appended paper, designated as Papers 1–5. These papers collectively contribute to addressing the overarching research question: *"How to support the sensemaking of data in healthcare?"*. This thesis addresses this research question by drawing on five papers (Papers 1-5) across three different roles of data: as a practice, as a tool, and as algorithmic intelligence. As I will show later, each of these roles presents distinct challenges for sensemaking of data, raising the need to understand the sensemaking of data (interpretive support) and provide tailored support to ensure its alignment with context (contextual fit support). To tackle these dual challenges, the thesis adopts conceptual, processual, and design-science approaches that together illuminate and support the conditions under which data becomes meaningful and actionable in healthcare.

The thesis is structured around five papers (Papers 1-5) that focus on three complementary roles of data: as practice, tool, and algorithmic intelligence, and the interpretive and contextual challenges they entail.

As illustrated in Figure 1, each paper sits at the intersection of one or more data roles and contributes a distinct model to support the sensemaking of data:

Data as practice (Papers 2 and 5) treat data as an ensemble of people, technologies and repeated interpretive practices (Xu et al., 2014). *Paper 2* is a literature review which theorizes insights into what it means to "know" data, by exploring the roots of the concept "data knowledge" through interpretive practices. *Paper 5* is an interpretive study which theorizes and develops a process model of collaborative sensemaking of healthcare data in the context of precision public health. It does so by exploring how meaning of data is discovered collectively, especially when diverse healthcare experts operate with distinct expertise and partial knowledge about particular aspects of data insights in precision public health.

Data as a tool (Papers 3 and 4) treat data as a computational artifact whose structure and presentation must be carefully tailored to fit disease characteristics and needs of healthcare practitioners. Both papers focus on the proposed design-science information technology (IT) artifact, a tool for supporting the sensemaking of data for mental-health assessment by informing the design of data signal arrangements through context-sensitive theories. While *Paper 3* focuses on raising design requirements and their instantiation in the IT-artifact to support the sensemaking of healthcare practitioners for mental health assessment, *Paper 4* focuses on the evaluation of the designed IT-artifact and the sensemaking processes with data as a tool.

Data as algorithmic intelligence (Papers 1, 3 and 4), treat data as algorithmic derived outputs. *Paper 1* is a literature review of empirical studies, which develops a typology of responsible interpretation practices in different forms of human-AI collaborations. The practical usefulness of the typology was shown through applying it to the empirical findings of a case involving AI-assisted medical diagnosis. As an algorithmic output may be visualized within a tool, *Paper 3 and 4* proposes and evaluates design requirements and IT-artifact to support the sensemaking of algorithmic-derived data outputs to support mental health assessments, by going beyond to just presenting a single decision from AI. *Paper 4* further provides an understanding on sensemaking processes when AI is a component in the tool.

This thesis adopts a multimodal approach to explore how the sensemaking of data can be supported in context-sensitive environments such as healthcare. The contribution of this thesis is the development of multi-perspective supports of sensemaking of data in healthcare which are theoretically grounded and practically oriented. Each of the included papers provides a distinct but complementary perspective: a conceptual model of data knowledge *(Paper 2)*, a typology of narrative responsibility in human-AI collaborations *(Paper 1),* a process model capturing the collaborative dynamics of sensemaking over time *(Paper 5)*, and a design-science artifact informed by context-sensitive theories for arranging and visualizing data signals *(Papers 3 and 4)*. This is presented in Figure 1.

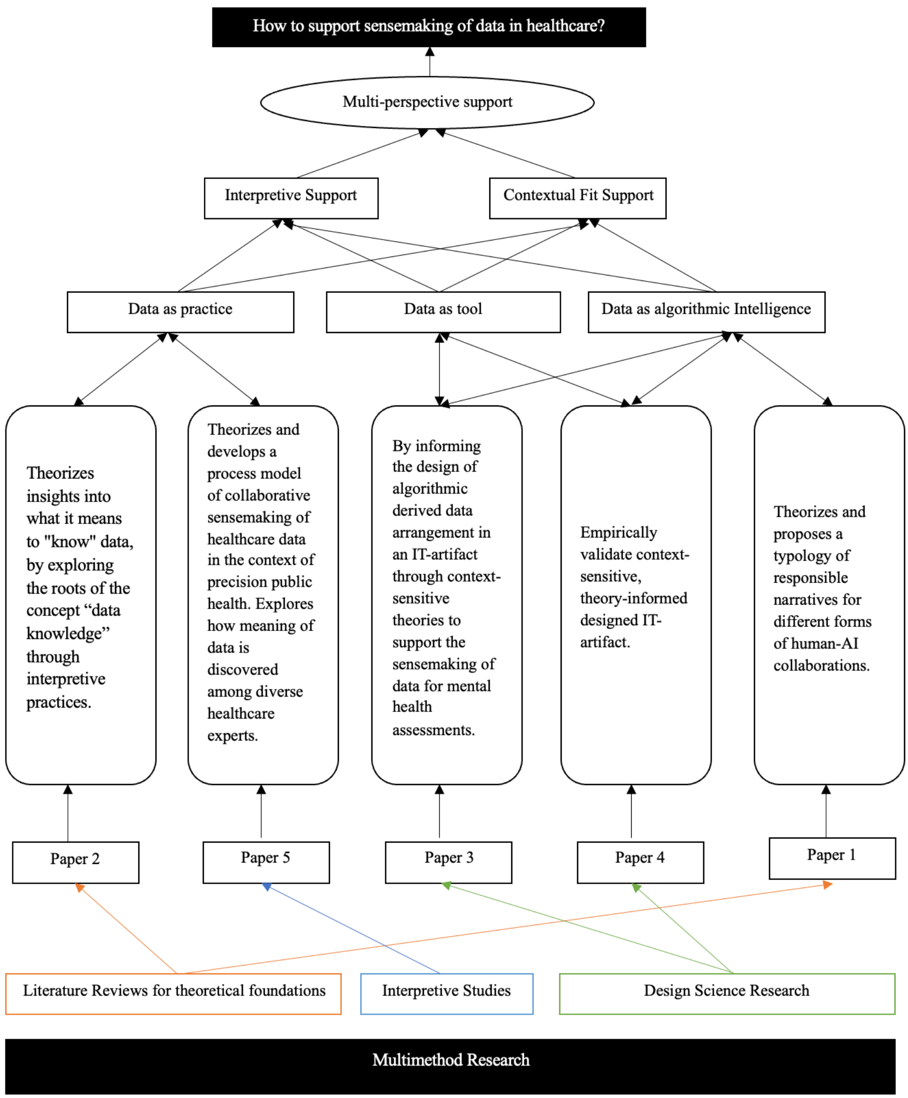

Figure 1 Research approach framework
This Figure represents the research approach in this thesis

Drawing from socio-technical axis of cohesion (Sarker et al., 2019) and rooted in the IS concern with how technologies shape sensemaking of data (Aaltonen et al., 2023; Lycett, 2013), the thesis builds on Orlikowski and Iacono's (2001) IT artifact views and Xu et al.'s (2024) data role typology. It goes further by emphasizing the support needed for sensemaking in healthcare across different roles of data, showing how practitioners come to know what data matters, how systems shape sensemaking of healthcare data, and how to design for supporting sensemaking of data for tailored healthcare assessments.

Theoretical Background

Sensemaking of data

Sensemaking has long been recognized as a key process in how individuals, groups and organizations understand and respond to the environment around them. It became a central topic in organizational research in the 1990s (Weick 1993; 1995), and has since been explored in fields like education, decision-making, and IS (Abbasi et al. 2018; Barney Tan et al. 2020, 2020; Lycett 2013; Maitlis and Christianson 2014). At its core, sensemaking is the process through which people interpret signals in their environment, assign meaning to them, and take action (Klein et al. 2006; Maitlis et al. 2013; Vlaar et al. 2008; Weick 1995). It is typically triggered by unexpected situations or ambiguity (Maitlis et al. 2013) and involves ongoing reflection, judgment, and collaboration (Coeckelbergh 2023; Weick 1993).

As technologies have advanced, the focus of sensemaking has shifted in making sense of data (Lycett 2013). Earlier, sensemaking focused on understanding and interpreting physical events or organizational signals (Weick 1995; Maitlis 2013) whereas with the modern contexts, it often require people to make sense of vast, complex, and rapidly changing data (Koesten et al. 2021; Lycett 2013). In this thesis, I focus specifically on the sensemaking of data, understood as the process of understanding, interpreting and evaluating data (Calvard 2016; Klein et al. 2007; Koesten et al. 2021; Lycett 2013; Marshan and Lycett 2016). This process forms an important part of reaching decisions (Abbasi et al. 2018; Sharma et al. 2014).

The literature shows that sensemaking of data involves more than identifying patterns or connecting data points (Klein et al. 2006; Lycett 2013; Sharma et al. 2014). It also requires knowing which data to prioritize, how to interpret it, and when to ignore what is irrelevant (Klein et al., 2006; Calvard, 2016). While sensemaking is sometimes presented as primarily a cognitive activity, it is also fundamentally social (Calvard 2016; Gagnon et al. 2025; Lycett 2013; Vlaar et al. 2008). People make sense of data together by discussing it, sharing interpretations, and forming collective judgments (Mesgari and Okoli 2019; Vlaar et al. 2008; Weick 1995).

Sensemaking of data, now increasingly unfolds in collaboration with technological systems. Dashboards, AI-driven suggestions, and visualizations offer new ways to explore information and highlight patterns (Davidson et al. n.d.; Gagnon et al. 2025; Kajtazi et al. 2023; Kitchens et al. 2024a; Lebovitz et al. 2021; Pieper and Gleasure n.d.; Pirolli and Card 2005; Steen et al. 2017). Such tools can expand users' attention and reveal signals that might otherwise go unnoticed (Gagnon et al. 2025; Lycett 2013). However, while these tools support the process of sensemaking, they cannot replace human judgment (Coeckelbergh 2023). Data still needs to be contextualized and interpreted, especially when it is incomplete, or generated in systems not designed for analytical use (Aaltonen et al. 2023; Holmes et al. 2021; Jones 2019).

A recurring challenge in the sensemaking of data is the absence or loss of contextual nuances (Aaltonen et al., 2023; Aaltonen & Penttinen, 2021; Calvard, 2016; LEE, 2003). Data does not carry meaning on its own. Rather its value comes from how it is used in a specific situation (Aaltonen et al. 2023; Jones 2019; Xu et al. 2024). Sensemaking is therefore shaped by the surrounding context, by the tools through which data is encountered, and by the perspectives and responsibilities of those engaging with it (Calvard, 2016; Gagnon et al., 2025; Pieper & Gleasure, 2025).

These challenges become even more pronounced when AI is involved. Studies show that professionals do not simply accept AI recommendations. Instead, they actively work with them by scrutinizing outputs, comparing them with their own reasoning, and adjusting decisions in response (Abdel-Karim et al. 2023; Gagnon et al. 2025; Jussupow et al. 2021; Lebovitz et al. 2021; Pieper and Gleasure n.d.). Sensemaking thus increasingly takes place through the interaction between human judgement and machine-generated outputs, an interaction that is especially consequential in context-sensitive domains such as healthcare.

In the following section, I turn to the healthcare setting to explore the sensemaking of data in this highly complex, dynamic, and deeply context-sensitive domain (Kay 2022). As I will show, understanding how data can be made sense of in such environments requires attention not only to what data represents, but also to how it is produced, how it is used, and how it interacts with both human and technological systems. As I explore in the next section, this complexity invites us to look more closely at how data is understood in practice: how it is used by humans, interpreted by machines, and embedded into practices.

Sensemaking of data in healthcare: a context-sensitive sensemaking process

Settings like healthcare are consistently mindful of different or surprising signals, and are prepared to identify abnormalities in their surroundings and respond accordingly (Faisal et al. 2013; Lee and Yee 2020; Maitlis et al. 2013; Pieper and Gleasure n.d.; Yeow and Chua 2020). In such settings, sensemaking is crucial, but also inherently complex (Kay 2022). Sensemaking research emphasizes that this process is driven more by plausibility than accuracy (Helms et al. 2010). This means that individuals often rely on signals that feel reasonable within a given situation, which can lead to flawed interpretations (Helms et al. 2010a). As Helms et al. caution, this tendency may "eliminate what is accurate and potentially rely on faulty decision making in determining what is right or wrong" (Helms et al. 2010a, p.185). Therefore, it is essential to have a careful and context-sensitive sensemaking particularly in domains where consequences are significant, such as healthcare (Maitlis et al., 2013).

Compared with creative or exploratory domains, where sensemaking may be more open-ended and involves combining whatever signals in different ways, the healthcare context demands for interpretations that are precise, accountable, and cautious (Maitlis et al. 2013). Sensemaking in this setting tends to adopt more cautious and selective forms of the surrounding signals (Maitlis et al., 2013). During this process, sensemaking needs to occur through a careful and cautious examination of the surrounding signals, comparing the signals rather than simply combining them. Maitlis et al. (2013, p. 230) describe this as an iterative "either/or" process in which healthcare practitioners compare and evaluate different surrounding signals while remaining highly sensitive to inconsistencies. Practically, this requires determining which data points are clinically significant, which are irrelevant, and how the meaning of data may shift as new information emerges (Maitlis et al. 2013). These demands are heightened when data is incomplete, of different nature, ambiguous, or generated in ways that obscure its original context (Aaltonen et al. 2023; Lebovitz et al. 2021; Lycett 2013; Pieper and Gleasure n.d.).

A key reason why sensemaking of data in healthcare is particularly challenging is that data is deeply contextual (Jones 2019; LEE 2003), and clinicians must remain attentive to multiple aspects of that context when making decisions (Dolley 2018; Khoury et al. 2018; Maitlis et al. 2013; Zon et al. 2023). As Jones (2023) argues, data in any domain is always contextual, but in healthcare this contextuality is heightened due to the potential consequences of misinterpretation (Kay 2022). The same data point in healthcare such as a sensor reading, can carry entirely different implications depending on the disease, the stage of treatment or the patient's history in which it is reviewed (Xu et al. 2021; Zon et al. 2023). For example, as stated in in the introduction, a sensor data of heart rate of 160 beats per minute may be entirely normal if the patient is exercising (suggesting sinus tachycardia), but could signal a potentially life-threatening arrhythmia if recorded while the individual is resting or asleep (Zon et al. 2023). This illustrates that the meaning of a data point depends on how and when it is produced, and on the clinical situation in which it is interpreted. As a result, sensemaking of data in healthcare requires not only technical competence but also familiarity with contextual details that are frequently absent from the data (Aaltonen et al., 2023; Pieper & Gleasure, 2025). These include disease context, patient characteristics, documentation practices, and medication-specific considerations that shape how data is read, shared, and used to inform decisions (Kay 2022). Misalignment between data and its use context, whether due to limited clinical awareness, over-reliance on technologies, or fragmented practices poses significant risks (Lycett, 2013).

Sensemaking in healthcare is further complicated by its inherently socio-technical nature. Human expertise and technological systems are tightly interwoven, and data interpretation is increasingly mediated by tools such as electronic health records, decision support systems, or AI systems (Bardhan et al., 2025). These systems influence what becomes visible, what is prioritized, and what counts as useful for decision making (Lycett, 2013). Yet, if they are not carefully integrated into clinical practice, they can reinforce abstraction and obscure the very context needed to make sense of data appropriately (Bardhan et al., 2025). As Pieper et al. (2025) show, AI systems in healthcare shape how problems are framed, what signals are elevated, and which pathways are taken in forming conclusions. Their findings suggest that AI outputs must be interpreted and situated within ongoing healthcare practice, rather than treated as independent sources of truth (Pieper et al. 2025).

Importantly, data in healthcare is used differently depending on who engages with it, how it is represented, and what purposes it serves (Aaltonen et al., 2023; Lycett, 2013). Data may function as a structured tool for decision-making, become part of everyday routines and collaborative practices, or be embedded within algorithmic systems that simulate aspects of human reasoning (Xu et al., 2024). In the next section, you can see how each of these roles creates distinct challenges for how data is interpreted and acted upon. As Xu et al. (2024) and Jones (2019) suggest, meaning does not reside in the data alone, it is constructed in use, often through interactions between professionals, systems, and technologies. This view aligns with socio-technical foundations of IS research, which emphasize the importance of understanding how meaning is created through interdependent human and technological relations (Orlikowski & Iacono, 2001; Sarker et al., 2019).

In healthcare, supporting effective sensemaking of data is not simply a technical matter but rather a necessary condition for responsible and informed care. Support requires more than access to data. It involves enabling reflective, context-aware engagement with data and responsiveness to clinical realities (Baird et al. 2025; Bardhan et al. 2025; Karahanna et al. 2006). Without such support, there is a risk of amplifying uncertainty, reinforcing bias, or undermining the nuanced judgment that healthcare decisions demand (Ademaj et al., 2025). As data becomes increasingly central to medical work, the challenge is not just to generate more of it, but to ensure that it can be understood and used meaningfully, in ways that respect both the complexity of the domain and the expertise of those working within it (Gagnon et al. 2025; Yeow and Chua 2020).

Sensemaking of data in healthcare from multi-perspectives

To support the sensemaking of data in healthcare, it is important to understand how data is used in organizations, how people interact with it, and how technological systems shape that interaction. Recent IS research shows that data can take on different roles in organizations, including data as a tool, data as a practice from a collaboration between experts and data as algorithmic intelligence (Xu et al., 2024). Given the way data are re-presented and used across different roles, different sensemaking challenges can arise in practice. Building on the Orlikowski and Iacono (2001) call to study IT through multiple conceptual lenses, and on Xu et al.'s (2024) role-based view of data, this thesis approaches sensemaking of data as a dynamic, socio-technical, and context-dependent process rather than the interpretation of "raw" data points. From this perspective, data become meaningful through interaction, interpretation, and situated use, and this process differs depending on how data are framed, produced, and applied in practice (Jones, 2019; Xu et al, 2024).

To clarify how different kinds of support may be needed, this thesis groups relevant literature into three clusters aligned with these roles: data as a tool, data as a practice, and data as algorithmic intelligence and adopts this lens to offer a more integrated perspective on supporting the sensemaking of data in healthcare. The three clusters are presented in Table 1 along with key characteristics, challenges and references to their applicable literature.

Table 1. Three literature clusters on sensemaking of data challenges
The table represents the different sensemaking of data challenges based on different data roles (Xu et al. 2024).

Data Roles	Key characteristics	Sensemaking of data challenges in healthcare	Existing literature
Data as tool	An engineered artifact created to serve specific organizational goals (Xu et al. 2024). These tools frame what is seen, compared, and emphasized.	Challenges arise from how well tools are aligned with the usage context and how well are they designed to support the user's ability to interpret, contextualize, and act on data.	(Abbasi et al. 2018; Al-Hajj et al. 2017; Baird et al. 2025; Bankuoru Egala and Liang 2023; Bardhan et al. 2020, 2025; Jones 2019; Kitchens et al. 2024a; Lycett 2013; Streeb et al. 2018; Xu et al. 2024).
Data as practice	Data becomes meaningful through repeated, collective use (Xu et al. 2024). Data is embedded in organizational routines and teamwork (Xu et al. 2024).	Raises issues to how the meaning of data is discovered in such settings where they is an interplay between groups of diverse healthcare experts and tools.	(Aaltonen et al. 2023; Alaimo and Kallinikos 2022; Holmes et al. 2021; Keller 2017; Khoury et al. 2018; Pieper and Gleasure n.d.; Xu et al. 2024).
Data as algortihmic intelligence	Data is processed through AI systems that generate their own interpretations in the form of predictions, classifications, or recommendations (Xu et al. 2024). Following Rieder et al. (2025), AI participates in practice by producing and prioritising meaning.	Sensemaking of data is hindered when healthcare experts must rely on systems whose logic they cannot fully see, question, or control, raising concerns about trust and limited sensemaking of data.	(Coeckelbergh 2023; Gagnon et al. 2025; Jussupow et al. 2021; Lebovitz et al. 2021; Lycett 2013; Pieper and Gleasure n.d.; Rieder et al. 2025; Xu et al. 2024).

Data as a tool - According to Xu et al. (2024), data is understood as an engineered artifact created to serve specific goals. This view aligns with work that treats information technology as a designed artefact that organizations and users can adapt to suit particular aims and contexts (Jones 2019; Orlikowski and Iacono 2001; Xu et al. 2021). When data is viewed as a tool, it is deliberately structured to support decision-making, improve performance, or enhance operational efficiency. Data is therefore expected to “perform” in ways that serve the intentions of designers and users (Jones 2019; Orlikowski and Iacono 2001; Xu et al. 2021). Examples of existing work in accordance to this view are data-driven decision making tools or data analytics tools that structure how data is presented and used (Abbasi et al., 2018; Abouzahra et al., 2024; Kitchens et al., 2024).

In healthcare, this view is highly visible because data is frequently encountered through computational tools that clinicians use to support judgement and action (Bardhan et al. 2020). Such tools are widely embedded in clinical work (Bardhan et al. 2020), including clinical decision-support systems, mobile applications, visual analytics platforms, and diagnostic tools that position data as a functional IT-artifact intended to support professional decision making (Abdel-Karim et al. 2023; Al-Hajj et al. 2017; Jussupow et al. 2021, 2022; Lebovitz n.d.; Pieper and Gleasure n.d.). However, using data in this way introduces several challenges to sensemaking of data. Tools usually visualizing data in a particular way, shape sensemaking by organizing and interpretively framing what counts as relevant, how comparisons between data are made, and which patterns become salient (Abbasi et al. 2018; Lycett 2013; Streeb et al. 2018). In doing so, they can shift parts of the cognitive effort from the clinician to the artifact itself (Lycett, 2013; Pirolli & Card, 2005). This makes sensemaking dependent on how the tool represents, filters, and connects this data (Abbasi et al. 2018; Lycett 2013; Streeb et al. 2018).

Empirical work illustrates how tool design influence whether tools support sensemaking. For instance, Abouzahra et al. (2024) show that the continued use of clinical decision support systems depends on their alignment with physicians’ routines, task relevance, and trustworthiness underscoring how tools must be meaningfully integrated into everyday clinical practice to support effective sensemaking. Similarly, Bankuoru Egala and Liang (2023) demonstrate that clinicians often exhibit algorithm aversion, rejecting even accurate mobile clinical decision support systems due to concerns about transparency, autonomy, or overreliance on technology. These studies highlight that when data is treated as a tool, sensemaking challenges are deeply tied to how the system fits into human work practices, and whether it supports or constrains clinical agency (Ademaj, Chowdhury, et al. 2025; Kay 2022; Pieper and Gleasure n.d.). Chen et al. (2011) extend this insight by discussing loose coupling in healthcare IS, showing how fragmented systems can impede coherent sensemaking across organizational units.

Moreover, visual analytics represents a particularly important class of tools because it is explicitly designed to support sensemaking through interactive visual representations of complex data representations (Baker et al. 2009; Keim et al. 2008). Visual analytics tools function as mediators between humans and data as they support navigation, exploration, and pattern detection by enabling users to interact with large datasets through computationally generated visual displays (Baker et al. 2009; Keim et al. 2008). As Keim et al. (2008, p.158) describe, visual analytics is "an integral approach to decision-making, combining visualization, human factors, and data analysis". Their role is to support sensemaking by allowing users to explore, manipulate, and detect patterns in the data. However, while visual analytics tools offer crucial support for understanding data, they also introduce specific challenges to the sensemaking process (Lycett 2013). First, users may experience cognitive overload, particularly under time pressure, which is common in healthcare settings (Al-Hajj et al. 2017; Faisal et al. 2013). In such conditions, clinicians may rely on surface-level impressions or jump to conclusions without fully engaging with the data (Streeb et al. 2018). Second, while visualizations are designed to support understanding of data, they often rely on heuristics and perceptual cues, which can lead to interpretive biases (Baker et al. 2009; Streeb et al. 2018, 2021a). Users may selectively focus on data that confirms their expectations, overlooking contradictory or subtle signals (Keim et al., 2008; Streeb et al., 2021). Third, visual design choices shape what users see or fail to see (Gagnon et al. 2025; Streeb et al. 2021b). Issues such as inattentional blindness, information overload, and misleading layouts can obscure critical insights even when the data is technically present (Gagnon et al. 2025; Streeb et al. 2021b). This highlights that even as visual analytics serves as a powerful mediator between humans and data, its effectiveness relies on the user's capacity to critically interpret visual outputs and remain aware of their cognitive limitations. Thus, while visual analytics enhances access to data insights, it also underscores the need for tools that support careful reflection, reduce noise, and guide users toward careful decision making.

This body of literature emphasizes that data as tool systems are most effective when they support interpretation and are aligned with existing professional routines. Viewing data as a tool highlights its role in the process of sensemaking. From this perspective, sensemaking of data is shaped by the context, goals, and practices of those using it (Jones 2019; Xu et al. 2024). Just as tools are used to interact with and shape the material world, data serves as an intermediary that helps individuals and organizations navigate, understand, and make decisions within complex environments (Klein et al. 2007; Lycett 2013; Orlikowski and Iacono 2001). Through choices such as what is shown, how data is grouped, or which trends are highlighted, they influence what users notice and how they compare information (Lycett 2013).

A key risk is that these representations can create a misleading sense of clarity, making complex situations appear simpler or more certain than they really are (Lycett 2013.). The subjective and adaptable nature of tool-based data use reinforces the point that meaning is constructed rather than given, making design a central element in how sensemaking can be supported (Abbasi et al. 2018). Accordingly, the literature suggests that tools should support rather than replace professional judgement, encourage critical interpretation, and align with clinical reasoning and contextual needs (Keim et al. 2008; Lebovitz et al. 2021).

Data as* a *practice - According to Xu et al. (2024), the data-as-practice view understands data as something that becomes meaningful through use in collaboration, shaped by and shaping the ongoing relationship between technologies, people, and practices. This view focuses on how data and its meaning circulate in practice, produced and re-produced through routines, and tied to collective processes of learning and doing (Alaimo & Kallinikos, 2022; Xu et al., 2024). Data is therefore also shaped collectively through situated use within specific organizational and clinical contexts (Xu et al., 2024).

In healthcare, this perspective is particularly relevant because data circulates across roles, shifts, and systems (Gilson et al. 2021). When data becomes part of work in healthcare, the sensemaking of data happens between collaborations of the IT artifacts and the healthcare experts involved in using it (Barney Tan et al. 2020; Nakikj et al. 2023). As a result, sensemaking is about participating in the ongoing practices that give data its meaning (Calvard 2016). One major challenge in this context is that data has no clear meaning without context (Aaltonen et al. 2023; Jones 2019). Healthcare practitioners must consider where the data comes from, how it was generated, and whether it fits the situation they are currently dealing with (Khoury et al. 2019). However, depending on previous experiences each practitioner might have different views on data and share its meaning in different ways (Lycett, 2013).

Studies illustrate how interpretations differ across professional roles and settings. As Whitelock-Wainwright et al. (2022) show that doctors and surgeons interpret performance data differently depending on their role and local context, which adds complexity to decision-making. Pieper and Gleasure (2025), show that what counts as meaningful data for a healthcare expert may not be meaningful in the same way for non-clinical experts. While clinicians often foreground diagnostic and patient-specific context, non-clinical actors may attend to other aspects, such as operational metrics or system outputs (Pieper & Gleasure, 2025). This does not mean that one group is “right” and another is “wrong”, rather, it shows that data rarely contains a single, fixed truth. Meaning is shaped by responsibilities, expertise, and the need to collaborate across perspectives (Baird and Xia 2024; Naumova 2022).

Finally, the tools that shape how data is collected and shown also affect in collaborative sensemaking practices. Systems like electronic health records decide what gets recorded and how it is displayed (Keller 2017). This can hide key clinical information such as patient confusion during a telehealth visit because the system was not built to capture that kind of nuance (Holmes et al. 2021). In addition, there might be cases where other healthcare practitioners tend to register too much data in these or have individual preferences on data registration (Keller 2017). Holmes et al. (2021) point out that electronic health records are often designed for billing or documentation, not for helping clinicians sensemaking of data. Related concerns extend to AI systems when they become embedded in routine work. Lebovitz et al. (2021) add that AI systems trained on expert-labelled data may also miss the complexity of real clinical practice, especially when those labels are disconnected from daily workflows. Even when AI becomes part of diagnostic routines, as shown by Abdel-Karim et al. (2023), it takes time for clinicians to reflect on and adapt to these systems, building new habits around how they make sense of the output.

Altogether, this literature shows that sensemaking of data in healthcare is not just about "reading numbers or text." It is an ongoing, collaborative process shaped by context, communication across professional roles, coordination, and using the systems through which data is produced and shared. Without attention to these factors during the sensemaking process, data can be easily misunderstood even when it seems objective (Lyccet, 2013). In this way, the data-as-practice view reinforces that data is performed and interpreted through situated collaborative practice (Alaimo & Kallinikos 2022). Yet IS and healthcare literature needs a unified understanding of what it truly means to "know" data in these environments (Koukouvinou et al. 2023). The literature highlights issues of context-dependence, role-based interpretations and collective engagements.

Data as algorithmic intelligence - According to Xu et al. (2024), data-as-algorithmic-intelligence view focuses on algorithmic computation that evolves over time and simulates aspects of human intelligence in the sensemaking process (Gagnon et al. 2025; Gagnon and Regt 2020; Lycett 2013). In this view, data does not merely get displayed through an artefact, it is actively processed by different ML algorithms. ML systems identify patterns in large datasets and generate outputs such as predictions, classifications, or recommendations that shape what users see and how they act (Bauer et al., 2023; Coeckelbergh, 2023; Gagnon et al., 2025; Lycett, 2013).

This role is fundamentally different from the data-as-tool view. Much existing IS research still treats AI as a tool that operates within established human practices, where people remain the main source of judgement and control (Coeckelbergh 2023; Rieder et al. 2025). This framing assumes that work routines and institutional structures are relatively stable and that AI mainly supports what humans already do (Reider et al. 2025). However, recent research in IS suggests that this view is becoming limited. As AI systems increasingly learn, adapt, and produce outputs on their own, they begin to shape how work is done and how meaning is formed, rather than simply supporting existing practices (Rieder et al., 2025). Rieder et al. (2025), for example, show that while many domains still frame AI as an instrument that supports human work, emerging forms of AI increasingly act in ways that go beyond passive assistance. Drawing on developments in the art world, Rieder et al. (2025) argue that AI is moving along trajectories from being a tool, to a medium, and in some cases even to an entity that can independently generate, adapt, and circulate outputs, thereby reshaping human roles, practices, and institutional arrangements. This shift is important because it challenges the assumption that humans always remain the sole locus of agency and interpretation when working with AI (Coeckelbergh 2023). Instead, AI systems increasingly participate in social activity by producing outputs, shaping attention, and influencing how meaning and value are constructed (Ademaj, Chowdhury, et al. 2025; Rieder et al. 2025).

In healthcare, AI has not reached the stage of autonomous social actors, but it already exceeds the role of a simple representational tool. Machine-learning systems do not merely display data for human interpretation, they analyze, classify, and transform data into predictions and recommendations that augment clinicians' reasoning during health assessments (Lebovitz et al 2021). This makes AI fundamentally different from dashboards or reports which are intended to be used as representational forms of data to organise information for human sensemaking (Keim et al. 2008; Lebovitz et al. 2021). As a result, clinicians must interpret what the algorithm has already interpreted (Lycett, 2013). The primary sensemaking challenge is therefore algorithmic opacity (Lebovitz et al. 2021; Lycett 2013). Questions such as "Can healthcare practitioners understand what the model "saw" in the data?" or "why did it produce this particular output?" or "how should algorithmic predictions be combined with clinical expertise and patient-specific context?" may arise (Jiang et al., 2024; Khoury et al., 2018; Lebovitz et al., 2021).

In this view, data as algorithmic intelligence highlights the growing role of AI predictions in shaping how data is interpreted (Bauer et al. 2023; Coeckelbergh 2023; Gagnon et al. 2025; Lycett 2013). In healthcare, this is increasingly central to reaching diagnosis. Abdel-Karim et al. (2023) show that AI systems may prompt reflection and a “second-opinion” reasoning among clinicians, influencing how diagnostic conclusions are formed. However, IS research also highlights important limitations and risks. Jussupow et al. (2021) and Lebovitz et al. (2021) caution that AI systems are only as reliable as the data and labels used to train them. They show that data that may embed biases, strip away context, or rely on uncertain ground truths ((Lebovitz et al. 2021; Jussupow et al. 2021). This raises serious challenges as even technically accurate systems can be misused if the sensemaking of the AI outputs is not well understood or critically assessed (Lebovitz et al. 2021; Jussupow et al. 2021).

Furthermore, from a sensemaking perspective, the key issue is therefore not simply whether the algorithm is accurate, but it is mostly a human process that needs to be supported. And this is whether the AI outputs can be understood, questioned, and responsibly used upon in different healthcare contexts (Lebovitz et al. 2021; Jussupow et al. 2021). As Coeckelbergh (2023) notes, experts do not simply accept or reject AI predictions, they rather “make sense of AI, with AI, and, if necessary, against AI” (p. 2438). This reinforces that when data takes the form of algorithmic intelligence, sensemaking involves a distinct set of challenges related to responsibility in narratives (Coeckelbergh 2023).

The aforementioned data roles, make clear that sensemaking of data is a multi-level, multi-actor, and multi-system process. The literature reveals a close interplay between humans, social processes, and digital technologies in shaping the sensemaking of data to reach decisions. Common themes include the need for alignment between data representations and human expertise, the importance of iterative and collaborative sensemaking in healthcare settings, and the emerging challenges (and adaptations) when AI and other analytical tools confront healthcare practitioners. At the same time, much of the existing research tends to focus on isolated elements, such as individual cognition, cue recognition, or specific system designs. However, in healthcare, supporting data sensemaking requires awareness to all these different aspects (Baird et al., 2025).

Building on this understanding, this thesis proposes a multi-perspective approach. Each of the papers adopts a different view of data, drawing on Xu et al., (2024), to explore and support sensemaking of data from different perspectives. The reviewed literature not only shows what we know about sensemaking of data in IS but also points to future research needs. As data volumes grow and algorithms become more entrenched in healthcare settings, further investigation is needed into topics such as collaborative sensemaking of data in groups of healthcare experts, the role of narrative and storytelling in these collaborations, and techniques to improve human-AI sensemaking.

To answer the research question: "*How to support sensemaking of data in healthcare?*", this thesis draws on multiple theoretical and methodological perspectives. Across five studies, it engages with different aspects of sensemaking of data: as clinical sensemaking supported by tool design (Paper 3,4), as collaborative interpretation embedded in diverse healthcare practice (Paper 5), as human-AI interaction requiring narrative responsibility (Paper 1), and as theorizing data knowledge through data practices (Paper 2). Each of these papers highlight different perspectives of support to the sensemaking of data in healthcare.

A theoretical framework on supporting the sensemaking of data in healthcare

I now introduce a theoretical framework to structure the different forms of support needed for the sensemaking of data in healthcare, which at the same time presents the entry points that shaped my research approach. This framework was developed in response to the growing complexity of data sensemaking in healthcare, and the diverse roles that data play: as practice, as tool, and as algorithmic intelligence.

To address the core research question on *"How to support the sensemaking of data in healthcare"* this framework identifies two foundational dimensions of sensemaking support: *interpretive support* and *contextual fit support*, see Table 2.

Tabel 2. A two dimensional theoretical framework
The table represents a theoretical framework for guiding the support of sensemaking of data in healthcare

		Data Roles		
		Practice	**Tool**	**Algorithmic Intelligence**
Sensemaking Support Dimensions	**Interpretive Support**	**1) Focus:** Explore how practitioner come to know data ⬇ **Paper 2:** Foundational insights into what it means to "know" data, etymological roots of interpretive practices. --- 2) **Focus:** Explores how sensemaking unfolds across professionals, data sources, and systems. ⬇ **Paper 5:** Providing a process model of how collaborative sensemaking of data unfolds in diverse experts in precision public health context. **Collaborative process framing:** interpretive support for discovering meaning in dynamic, interdisciplinary contexts.	**Focus**: Explore how tools can be designed to support the sensemaking of data. ⬇ **Paper 3,4:** Interpreting how sensemaking happens through kernel theories and proposing design requirements to support sensemaking of multimodal data for mental health assessments. **Computational framing:** show how can tools help healthcare practitioners navigate complex data and identify patterns across modalities and time.	**1) Focus**: Explore how data interpretation happens in human-AI collaborations. ⬇ **Paper 1:** Explores how interpretive patterns vary across forms of human-AI collaborations. --- **2)Focus:** Exploring computational interpretation of ML-derived data outputs in healthcare. ⬇ **Paper 3,4:** Understanding how ML-derived data manifest and can be interpreted computationally to better support sensemaking of data for mental health assessment.

	Data Roles			
		Practice	**Tool**	**Algorithmic Intelligence**
	Contextual Fit Support	**Focus:** nuanced understanding of data knowledge. **Paper 2:** reflects how data is entangled with workflows, organizational constrains and tacit expertise. **Focus**: how context becomes embedded in data through collaborative practices. **Paper 5:** Providing a stage wise process model, showing the situated nuances of sensemaking of data.	**Focus**: Context-sensitive theory informed design, instantiation and evaluation. **Paper 3,4:** foregrounds what is needed in the mental health assessment context and tests whether these needs are supported through the proposed design IT-artifact.	**Focus:** tailored support for different forms of human-AI collaboration. **Paper 1:** provides a typology of responsible narratives for different forms of human-AI collaborations.
RESEARCH CONTRIBUTIONS		**THEORY-BASED SUPPORT**	**THEORY-INFOMED PRACTICAL SUPPORT**	**BOTH**

The decision to focus on these two forms of support for sensemaking of data is grounded in the literature and in the challenges previously summarized in Table 1. Sensemaking of data in healthcare is widely understood to be highly context sensitive (Maitlis 2013). As I mentioned, data does not carry meaning on its own (Calvard 2016), it only becomes meaningful when it is made sense of within specific clinical situations or disease characteristics (Zon et al. 2023). Furthermore, healthcare problems require more than one single solution (Baird et al., 2025). This led me to ask not only how sensemaking happens, but also what is needed to support it so that sensemaking of data can be used in clinical settings. I therefore argue that supporting sensemaking of data cannot rely on a single perspective. Instead, it requires an overall multi-perspective form of support.

From this perspective, two complementary forms of support emerged. *Interpretive support* focuses on understanding how sensemaking unfolds by making visible the work through which data becomes meaningful across roles, tools, and alignments. C*ontextual fit support* focuses on providing tailored support based on what is needed for specific disease contexts. These dimensions are especially important in healthcare, where understanding how sensemaking works must go hand in hand with understanding contextual details that are often missing from data itself but are essential for decision-making (Baird et al., 2025; Aaltonen et al., 2023 These two dimensions guide both the analytical lens and the research design throughout this dissertation, as developed in the following chapters.

Interpretive support emerged in response to a first cluster of challenges that becomes visible across the different roles data takes in healthcare: data as practice, as tool, and as algorithmic intelligence, namely the interpretive complexity of sensemaking. In the previous section, this thesis showed that in healthcare, data is made sense of through collaboration among healthcare practitioners, representations in tools and algorithmic recommendations, each bringing different forms of expertise, design challenges, and accountability. While interpretation is often treated in IS literature as a primarily technical or cognitive task (Lycett, 2013; Pirolli & Card, 2005), this framing overlooks how data meaning is co-constructed, socially negotiated, and situated in healthcare practice (Jones, 2019; Alaimo & Kallinikos, 2022). In the *data-as-practice* view, interpretive support must address how data becomes meaningful through everyday routines and collaborative interactions (Parmiggiani et al., 2022; Gherardi, 2000). In contrast, the *data-as-tool* view emphasizes how designed artifacts such as visual dashboards or decision-support systems shape the interpretive process calling for support mechanisms that enhance clarity, reduce cognitive load, and guide pattern recognition (Baird et al., 2025; Keim et al., 2008). Finally, within the *data-as-algorithmic intelligence* view, interpretive support must address the challenges of understanding and trusting machine-derived outputs, requiring new forms of responsible interaction between humans and intelligent systems (Lebovitz et al., 2021; Abdel-Karim et al., 2023). Recognizing these differences, I conceptualized interpretive support as an exploratory form of assistance that adapts to the distinct challenges embedded in each role of data use.

Interpretive support, as developed in this framework, addresses the need to understand how sensemaking of data happens in healthcare. It makes visible the supporting mechanisms and processes through which practitioners come to understand data. It therefore concerns the exploratory work required to make data meaningful and usable, particularly in environments characterized by complex expert interaction, complex forms of ML-derived data that require arrangement, and evolving relationships between experts and ML-derived outputs (Aaltonen et al. 2023; Baird et al. 2025; Jones 2019; Lycett 2013). Across the three roles of data, interpretive support assumes distinct roles:

- For *data-as-practice*, interpretive support focuses on two related needs. First, it requires clarity about what it means to *know* data in healthcare as a socially constructed and interpretively framed phenomenon. This need arises because sensemaking in healthcare is not only a matter of analyzing datasets, but of interpreting complex, dynamic, and often ambiguous information from healthcare experts who do not have technical skills. The data-as-practice view emphasizes that data is constructed, mediated, and used within routines, interpretive efforts, and contextual negotiations (Alaimo and Kallinikos 2022; Parmiggiani et al. 2022), which raises the need to move beyond hierarchical models of data-information-knowledge (Ackoff 1989). *Paper 2* contributes by uncovering the foundations of knowing data, what it means to "know" data through an etymological framing of data practices that shape how data becomes "known." Second, interpretive support focuses on making visible the way meaning of data is made sense of collectively especially when diverse healthcare experts operate with partial knowledge or limited expertise *(Paper 5).* This guides towards a collaborative sensemaking process framing.
- For *data-as-tool*, interpretive support focuses on how tools can be designed to support sensemaking of data. This addresses recent calls in healthcare IS research for advancing "the optimal use of visualizations to reduce cognitive load and increase the efficacy of health analytics output use by clinicians" (Baird et al., 2025, p.576). More specifically, it explores identifying design requirements and propose IT-artifact to navigate ambiguity in complex multimodal data environments for mental health assessments *(Paper 3 and 4).* This guided towards the need for designing tools that can help healthcare practitioners make sense of complex data and identify patterns across modalities and time. This makes visible the mechanisms through which tools can support the sensemaking of data for assessments, an important part of diagnosis in healthcare.

- For *data-as-algorithmic intelligence*, interpretive support focuses on two related needs. First, it explores how data narratives happens across different forms of human-AI collaboration. There is a recent call by healthcare IS research to understand "this changing nature in the distribution of rights and responsibilities between humans and IS that augment or automate decision-making opens a fascinating new array of research questions" (Baird et al., 2025, p. 578). *Paper 1* contributes by showing how interpretive patterns vary across collaboration forms, showing how responsibility is constructed during human-AI collaborations. Second, interpretive support also addresses how ML-derived outputs can be interpreted computationally to better support sensemaking of data, including how algorithmic outputs can be made more interpretable in practice *(Papers 3 and 4).*

In parallel, ***contextual fit support*** emerged in response to a second cluster of challenges that also becomes visible across the different roles data takes in healthcare, namely the context sensitivity of sensemaking. More specifically, it emerged from the recognition that the meaning and usefulness of data in healthcare depends not only on understanding how interpretation happens, but also on providing the situated nuances on what is needed to align with the practical, organizational, and clinical realities of specific contexts (Jones, 2019; Khoury et al., 2018). Contextual fit support therefore provides tailored solutions that make explicit the disease-specific characteristics, population needs and situated demands of clinical work. This need is crucial because healthcare is not a one-size-fits-all environment (Baird eta al., 2025). Sensemaking support must therefore be carefully tailored not only to "what data" is used but to how it used, interpreted with others and designed, by whom, and in which specific setting. It emphasizes the appropriateness and usability of data-driven insights within specific healthcare settings. Depending on the way data is viewed, this support can be studied by showing awareness on how sensemaking of data processes are tailored to disease-specific reasoning and on designing tools to tailored healthcare needs, more specifically disease context. Contextual fit, in turn, must be take into consideration the nuances of the healthcare context (Baird et al. 2025) because the appropriateness of any sensemaking support is deeply dependent on healthcare practices, disease characteristics, the sources from where the data comes from (Jones 2019; Khoury et al. 2018) and how it is processed and the roles engaged in making sense of data (Coeckelbergh 2023; Mesgari and Okoli 2019).

Recognizing that what is needed differs across roles of data, I conceptualize contextual fit support as operating through three types of contributions:

- For *data-as-practice*, contextual fit support focuses on two parts. First it focuses on the need for a nuanced understanding of data knowledge focusing on the different practices *(Paper 2).* Second, it directs attention to the diverse and shifting forms in which data appears in these settings and to what is required to make sense of it in context. Specifically, it explores how contextually grounded interactions shape the discovery of relevant data insights in precision health in different stages *(Paper 5).* This motivates a phronesis-informed process model which is known as practical wisdom (Dalal & Pauleen, 2019), bringing attention to nuances of what it needs to remain contextually aware in a context-sensitive area such as precision public health.
- For *data-as-tool*, contextual fit support focuses on providing what is needed to support sensemaking through design of IT-artifacts that are tailored to specific disease contexts, and on testing whether the tool supports these needs in practice. More specifically, it applies context-sensitive framings to inform the design of IT artifacts for mental health assessments *(Paper 3)* and by evaluating whether these designs support the requirements of that domain *(Paper 4).* In this view, contextual fit is demonstrated through kernel theories that ground design choices (Gregor et al. 2020) which are context-sensitive, but also through evaluation of whether the tool is effective in supporting sensemaking in a particular disease context.
- For *data-as-algorithmic intelligence*, contextual fit support focuses on providing tailored support for different forms of human-AI collaborations. More specifically, it provides what is needed through alignment across different forms of human-AI collaboration *(Paper 1).* This ensures that algorithmically shaped decisions remain anchored in situated context appropriateness, recognizing that different AI types and uses require different kinds of contextual sensitivity and situational alignment.

In this framework, I have explored two dimensions of sensemaking support that have different levels of complexity. To operationalize this framing, I developed a matrix that maps interpretive support and contextual fit support across the three views of data: practice, tool, and algorithmic intelligence, see Table 2. Each cell represents a distinct sensemaking demand shaped by the role of data and by the type of support required.

- *Data-as-practice* highlights the embeddedness of sensemaking in routine, collaborative, and often tacit interactions. *Interpretive support* provides an overall view of how sensemaking unfolds in practice, while *contextual fit support* provides tailored guidance on what is needed to remain contextually aware across stages in a context-sensitive area such as precision public health.

- *Data-as-tool* emphasizes the need to focus on the design of the IT-artifact. *Interpretive support* reveals tool design through kernel theories. *Contextual fit support* provides tailored, disease-specific design and evaluation that tests whether the tool supports what is needed in that clinical domain.
- *Data-as-algorithmic intelligence* foregrounds concerns of interpretive responsibility between humans and AI. *Interpretive support* explores how interpretations are formed with and through AI, including how AI contributes to or shapes interpretive narratives. *Contextual fit support* provides tailored support for each form of human-AI collaboration.

This dissertation aims to understand how to support the sensemaking of data in context-sensitive healthcare domains by exploring the different roles of data as practice, as tool, and as algorithmic intelligence. Building on the recognition that healthcare sensemaking is marked by interpretive uncertainty and contextual complexity (Baird et al. 2025), the thesis proposes that sensemaking of data support must be twofold: (1) understanding how sensemaking happens *(interpretive support)* and 2) providing tailored support for specific contexts *(contextual fit support),* by foregrounding the nuances of disease contexts and specifying what is needed in particular disease and care contexts so that sensemaking can be tailored to clinical realities and disease specific characteristics.

The dissertation responds through a multi-perspective and multi-method approach, offering both theory-based insights, such as conceptual models *(Paper 1,2),* process models *(Paper 5)* and theory-informed practical-oriented solutions *(Paper 3,4)*, such as the design and evaluation of IT artifacts that enhance interpretive clarity or contextual fit. Across all views of data and both forms of support, each paper in this dissertation contributes either by developing new theoretical understandings or by applying existing theory to create actionable design principles and frameworks for responsible, situated data use in healthcare. This framework provides a foundation for analyzing the empirical studies in this dissertation and explains why a multi-method approach is necessary to address the research question (for more details, see the next chapter: Methodology).

Positioning within Information Systems discipline

IS research is fundamentally concerned with the design, use and consequences of digital technologies in organizational and societal context (Orlikowski & Iacono, 2001). Sarker et al. (2019) shows that strong IS studies attend simultaneously to the social, the technical, and the ties that bind them, rather than privileging one side over the other. This thesis is positioned at the intersection of exploring how data becomes meaningful in healthcare by studying how digital artifacts, expert judgment, and clinical contexts come together in the process of sensemaking.

Specifically, by analyzing data through three lenses: as practice, as tool, and as algorithmic intelligence, the dissertation shows how different roles of data give rise to distinct sensemaking challenges. Each data role requires its own form of interpretive and contextual fit. In doing so, the thesis operationalizes the axis of cohesion (Sarker et al. 2019) across structure (data practices), agency (practitioner judgment and algorithmic mediation used to process the data), practice (IT-artifacts designed to support sensemaking of data), and outcome (context-sensitive decision quality and patient safety).

Furthermore, in response to Lee et al. (2021) concerns that much IS theory risks losing practical relevance, this thesis moves toward visionary goals as suggested by IS research, offering both theory-based insights (e.g., conceptual framings and process models) and theory-informed practical tools (e.g., design and evaluation of IT artifacts) that aim to enhance how data can be meaningfully made sense in healthcare.

Moreover, it contributes to the growing IS conversation on data and sensemaking in complex environments. Abbasi et al. (2016) warn that big data analytics is often dominated by technical concerns, neglecting the social context in which data is interpreted. This thesis directly addresses that gap, showing that supporting sensemaking is less about the volume of data, and more about enabling its interpretive and contextual usability (Aaltonen et al. 2023; Dalal and Pauleen 2019). By focusing on how data becomes meaningful through collaboration, tool design, and human-AI collaboration, the thesis answers recent calls for socio-technical and context-sensitive IS research (Dalal and Pauleen 2019).

Finally, the thesis revisits a foundational concern raised by Orlikowski and Iacono (2001) the need to treat the IT artifact seriously rather than treating technology as a black box. By analyzing the design of tools as well as the collaborative healthcare work practices they mediate, the thesis keeps the IT-artifact and the data within it, at the center of the thesis. It examines the design of IT-artifact to support sensemaking, how meaning is collaboratively surfaced, and how data is made sense of with AI in collaboration. In conclusion, this thesis addresses central IS questions about how digital tools, healthcare expertise, and contextual complexity intertwine and how interpretive and contextual fit can be theoretically framed and practically supported across multiple data views.

Methodology

Multimethod research has become increasingly important in IS literature as researchers confront complex, multidimensional sociotechnical phenomena that resist explanation through a single methodological lens (Sarker et al. 2025). These approaches go beyond the limitations of single method designs by allowing one method to compensate for the limitations of another and to offer enriched insights (Sarker et al. 2025; Venkatesh et al. 2016). Traditionally, "mixed methods" has referred to the combination of qualitative and quantitative approaches (Venkatesh et al. 2013a, 2013b), and this remains foundational allowing for both empirical rigor and contextual nuance. However, in light of evolving methodological possibilities and data forms, scholars now advocate for a broader conceptualization under the term "multimethod," which accommodates a wider array of combinations, including design science, analytical modelling, computational techniques, interpretive studies, and action research (Sarker et al. 2025). Sarker et al. (2025) propose a framework to classify such studies along two key dimensions: the methodological distance between the approaches used (proximal vs. distal), and the nature of their integration (interlayered vs. intertwined).

This thesis adopts a “bridge” design, which is a multi-method approach where conceptually and technically distinct methods are interlayered to provide complementary perspectives (Sarker et al. 2025). By embracing the strengths of different methods, this research approach seeks not only to compensate for individual methodological limitations but to construct a more holistic and robust understanding.

Multimethod Research Design

This dissertation investigates how to support sensemaking of data in healthcare. As described in the previous chapter, sensemaking of data in healthcare is marked by complexity in interpretation and contextual fit with the disease, the diverse professionals engaged, the different ways data is viewed and the rising role of AI. Given this multifaceted complexity, a single method or perspective would be insufficient to capture the full richness of the sensemaking of data phenomenon. As recently conceptualized in IS, healthcare-based problems are, as Baird et al. (2025) emphasize, "often either multifaceted, localized, or conditional, and the identification of solutions often needs to be both exploratory and nuanced, where one solution is often not sufficient" (p. 578). This complexity demands an approach that can examine and support the different interpretive and contextual fit challenges of those data across different data views. Therefore, this dissertation adopts a multimethod research design, combining *literature review studies* and *interpretive studies* with *design science* to explore complex dynamics in healthcare data use. These two approaches come from different research traditions and use different types of data and reasoning, which makes them methodologically distant. Rather than merging them tightly, they serve for complementary reasoning, where each allows each to contribute separately to the overall understanding, an approach known as interlayered integration (Sarker et al., 2025). This combination helps address the research question from different perspectives, allowing the strengths of one method to complement the limitations of the other in understanding and supporting a phenomenon from multi-perspectives. By using this mixed approach, the study benefits from both rich, context-sensitive insights and more abstract, generalizable explanations, which is a strength of distal multimethod research (Sarker et al., 2025).

This dissertation adopts a multimethod research approach, motivated by the need to explore the *interpretive* and *contextual fit* dimensions of sensemaking, each of which demands both theoretical insight and practical intervention. As discussed later, the design of this approach allows to support sensemaking of data in healthcare from multiple conceptual and empirical points. This dissertation applies different methods to explore different roles of data: as practice, as tool, and as algorithmic intelligence and the corresponding forms of support required for their sensemaking. To do so, this dissertation lies on five distinct papers, each grounded in a different method, independently explore how to support sensemaking under different roles of data.

The inherent complexity of sensemaking of data in healthcare demands a research approach capable of comprehensively capturing its theoretical depth and practical intricacies. Adopting a multimethod research approach, this dissertation strategically aligns distinct methodological approaches: literature review and interpretive studies and design science research with quantitative methods for evaluating the designed artifact, to meet complementary theoretical and practical needs. Literature review studies *(Paper 1,2)* provide deep theoretical explanations from the existing literature, Interpretive studies

(Papers 5) provide deep phenomenon understanding from empirical settings, clarifying how meaning of data becomes meaningful through different practices. Complementing this, design-science studies *(Papers 3,4)* offer theory-driven practical, actionable guidance in the form of rigorously developed design requirements and IT-artifact explicitly targeting the support of sensemaking of data in mental health assessments. By integrating these two methodological strands, the thesis generates insights that are theoretically rigorous, practically applicable, and deeply engaged with the real-world context of healthcare sensemaking (see Table 3,4,5). This multimethod theoretical framework thereby justifies the necessity of multiple, distinct papers, showing clearly how methodological diversity is harnessed to produce richer and more nuanced theoretical and practical understanding.

The decision to use multiple methods stems from the dual nature of the derived theoretical framework developed in this work (see Table 2), which distinguishes between two fundamental forms of sensemaking support: interpretive support (exploratory) and contextual fit (nuanced). The diverse methodological choices made in each of the five distinct papers were thus necessary to address the multiple dimensions and complexities of sensemaking that manifest differently across these data views.

Alignment with Research Question and Theoretical Framework

The overarching research question on "*how to support sensemaking of data in healthcare"* is inherently complex, exploratory, and multi-layered. The methods used in this dissertation are aligned with the different data roles and the specific interpretive and contextual fit needs that emerge. The theoretical framework developed in the previous Chapter, (see Table 2), identified key sensemaking focal points across data roles, each of which led to specific research questions and justified the method applied, (see Table 3). The theoretical framework distinguishes between interpretive support (understanding how) and contextual fit support (providing tailored support for specific contexts). Using the framework as a guide, the thesis necessitated to have different theoretical and empirical breadth. Each paper in the dissertation was methodologically and conceptually anchored in one or more cells of this framework.

Tabel 3. A multimethod approach

The table represents the connection between the guiding framework and the multimethod research approach

Paper	Data Role	Method	Focus	Form of Support	Reasoning of research approach	Contribution to research question
1	**Algorithmic Intelligence**	Literature Review/ Concept-based Analysis	Explores how data interpretation happens in AI-mediated environments and what is needed.	Interpretive Support & Contextual Fit	Requiring conceptual framing of the narrative forms in three forms of human-AI collaboration.	Explores how narrative responsibility (responsible data interpretation) manifests across different forms of human-AI collaboration for effective sensemaking.
2	**Practice**	Literature Review / Etymological Analysis	Foundations of how data becomes “known” through practice	Interpretive Support & Contextual Fit	Requiring a conceptual, etymological analysis of foundational interpretive assumptions.	Reveals deep interpretive roots of data understanding. Offers conceptual clarity that helps healthcare practitioners become aware of how interpretive efforts are shaped, not just by data itself, but by how they come to “know” data.

Paper	Data Role	Method	Focus	Form of support	Reasoning of research approach	Contribution to research question
3	**Tool / Algorithmic Intelligence**	Design Science – artifact development	Design requirements for IT tools for mental health data	Interpretive Support & Contextual Fit	Requiring theory-informed practical support through design science research.	Proposes artifact design to support sensemaking of multimodal and multi-model data.
4	**Tool / Algorithmic Intelligence**	Design Science - Quantitative Evaluation	Evaluation of IT artifact via user experiment	Interpretive Support & Contextual Fit	Requiring a user experiment and quantitative approaches.	Tests whether the designed IT-artifact support sensemaking needs in the context of mental health assessments.
5	**Practice**	Qualitative Study	Collaborative interpretation among diverse healthcare experts. Explore how the meaning of healthcare data becomes meaningful through collaborative data practices.	Interpretive Support & Contextual Fit	Requiring a qualitative approach of exploring collaborative sensemaking among diverse experts involved in precision public health.	Develops a phronesis process model of how collaborative sensemaking unfolds across different roles and knowledge types.

Nature of the Multimethod Design and Integration

As advised by recent reflections on multimethod research design (Sarker et al. 2025; Venkatesh et al. 2016), the value of multimethod work depend on the clarity with which the integration is conceptualized, used, and justified. In this dissertation, I adopt an interlayered integration strategy where distinct methods operate in parallel layers, each addressing specific challenges associated with different data views (practice, tool, algorithmic intelligence), and each contributing either theoretical insight, practical design guidance, or both.

This form of integration was particularly well-suited given the high methodological distance between the qualitative literature review studies (Paper 1, 2), interpretive studies (Papers 5) and the design science studies (Papers 3, 4). The literature review studies are qualitative and advance conceptual insights. The interpretive studies emphasize rich, empirical understanding of context-sensitive meaning-making processes. In contrast, the design science studies focus on shaping the future through IT-artifact construction and evaluation (Abbasi et al. 2024). Attempting to intertwine these methods, blending them within the same phase or logic of inquiry would risk epistemological incoherence. Instead, following (Sarker et al. 2025) I opted for a strategically interlayered approach, where each paper retains methodological autonomy, but collectively contributes to a coherent and complementary understanding of the broader phenomenon: supporting the sensemaking of data in healthcare.

The integration unfolds at the meta-inference level (Sarker et al. 2025), whereby the findings from each method inform and are guided by the conceptual framework introduced in the theoretical chapter 2. This framework structured along the dual axes of interpretive support and contextual fit provides the conceptual framework that binds the otherwise disparate methodological strands. Qualitative research on Papers 1, 2, and 5 provide depth into interpretive data practices and sociotechnical entanglements. Design science research on Papers 3 and 4 provide depth into exploring and proposing practical support for sensemaking of complex data in healthcare and aligning with disease-specific nuances of mental health context. The coherence of the dissertation lies not in methodological fusion, but in the complementarity of focus where each method offers a lens onto different dimensions of the same complex phenomenon (sensemaking of data), and each contributing toward answering the overall thesis research question.

Informed by recent IS framework for classifying multimethod research (Sarker et al. 2025), this dissertation adopts a bridge-type multimethod research approach, leveraging two distant in nature but complementary methodologies: interpretive research and design science research (DSR) to comprehensively understand and support sensemaking of data in healthcare. Rather than seeking iterative integration, the thesis deliberately uses the distinct methodological strengths and inferential nuances of each approach to aim for supporting the sensemaking of data in healthcare from multiple perspectives. Each method offers complementary insights into different dimensions of the sensemaking of data in healthcare.

The interpretive and design science methods are not integrated in a tightly intertwined manner (Sarker et al. 2025), but they are interlayered (Sarker et al. 2025) where each of these methods contribute to a deeper understanding of the phenomenon by addressing distinct research questions aligned with specific data views and forms of support. Therefore, each method addresses a specific facet of the problem space (Sarker et al. 2025; Venkatesh et al. 2016), shaped by how data is used, for what role and what form of support it demands.

Complementarity of the methods

This dissertation employs a multimethod research design, using distinct methods to explore and support the sensemaking of data in healthcare. The methodological strategy is complementary in two ways: (1) across different methodological types, and (2) within similar methodological types.

Complementarity across methodological types

Each method used in this dissertation was selected to fulfil a specific support role for the overarching research question: *"How to support sensemaking of data in healthcare?"* The literature reviews and interpretive studies *(Papers 1, 2, 5)* investigate different interpretive practices qualitatively to understand how sensemaking unfolds in complex sociotechnical contexts and exploring how data becomes meaningful, trusted, and accountable. These studies emphasize interpretability and contextual-fit support, uncovering deep conceptual and empirical insights into how meaning of data is discovered through different interpretive practices.

By contrast, the design science studies (Papers 3 and 4) focus on developing and evaluating practical interventions specifically IT-artifacts to enhance interpretability and contextual fit. The data collected to evaluate the proposed IT-artifact was analyzed using both quantitative and qualitative analysis.

Furthermore, these studies show how computational design can contribute to tailored sensemaking of data for specific disease context being informed by context-sensitive theories.

Importantly these methods serve complementary purposes: 1) Literature reviews and interpretive studies generate deeper understanding of sensemaking of data in healthcare by providing theoretical and empirical depth, while 2) design studies explore and evaluate computational interpretive ways to distinguish between important and non-important data supporting healthcare practitioners sensemaking. This complementarity strengthens the IS research by allowing both dimensions of the theoretical framework exploratory and nuanced support to be robustly addressed. This alignment allows the dissertation to respond to both exploratory and practical demands, producing meta-inferences (Sarker et al. 2025) about how different types of support enable sensemaking under varying data roles (practice, tool, and algorithmic intelligence). The multimethod approach provides complementary insight into what sensemaking of data involves across both interpretive and contextual fit dimensions, see Table 4.

Tabel 4. Complementarity across methodological types

This table represents complementarity across methodological types. Methodological distance: distal x Nature of Integration: Interlayered = Type of Multimethod: Bridge (Adapted from (Sarker et al. 2025).

	Dimensions	Interpretive Support	Contextual fit support	Method	Type of multi-method study
Complementary across methodological types	**Theory-based support**	**Papers 1, 2, 5** explore how sensemaking of data is discovered through different interpretive practices.	**Paper 1, 2, 5** the role of contextual fit while sensemaking of data.	**Literature reviews and Interpretive studies (Qualitative)**	**Bridge on answering the RQ from multiple perspectiv es**
	Theory-informed practical support	**Papers 3 and 4** explore how tools can be designed to support sensemaking of data in healthcare.	**Paper 3, 4** foregrounds what is needed in a specific disease context and tests whether these needs are supported through the proposed design IT-artifact.	**Design Science Research (Quantitativ e)**	

Complementarity of individual papers within methodological types

Beyond their across-type complementarity, the papers within each methodological type are themselves complementary.

The literature reviews and the interpretive studies type comprise three papers, each targeting a distinct interpretive challenge, engaging a different data view, and contributing unique conceptual clarity to the twofold support proposed in the theoretical framework. Collectively, these studies offer theory-based support by advancing conceptual *(Paper 1,2)* and empirical insights *(Paper 5)* into how data is made meaningful, interpreted, and embedded in clinical reasoning, see Table 5.

Tabel 5. Complementarity within qualitative studies
This table represents complementarity within qualitative studies.

Sensemaking Support Dimension	Paper	Focus	Theoretical Breadth	Method-ological Orientation	Complement-arity Explanation
Interpretive Support	Paper 1	Human-AI interpretive alignment	Develops a typology of responsible interpretation practices in human-AI collaborations.	Conceptual-Typological	Brings focus on responsibility and interpretability issues in sensemaking. It explains how data interpretation happens in AI-mediated environments and what is needed (narrative responsibility and typological differentiation) for effective interpretive sensemaking.

Sensemaking Support Dimension	Paper	Focus	Theoretical Breadth	Method-ological Orientation	Complement-arity Explanation
Interpretive Support	Paper 2	What it means to "know" data	Provides foundational etymological framing of interpretive practices of data.	Conceptual-Etymological	Establishes deep conceptual roots of data sensemaking, complementing more applied explorations.
	Paper 5	How meaning of data is discovered across expert groups	Offers a processual understanding of how collaborative sensemaking of data unfolds.	Empirical - Qualitative	Empirically shows how meaning and contextual appropriatenes s emerge in real settings.
Contextual Fit Support	Paper 1	Provides tailored support for sensemakin g in different forms of human-AI collaboration s	Highlights how interpretive patterns vary across forms of human-AI collaborations.	Conceptual-Typological	Brings a nuanced understanding on how to act in the different forms of human-AI collaborations.
	Paper 2	Provides a nuanced understandin g of data knowledge.	Reflects how data is entangled with workflows, organizational constrains and tacit expertise.	Conceptual-Etymological	Brings focus to the different aspects of data knowledge.
	Paper 5	Provides a phronesis process model which shows what is needed so that context is embedded in collaborative practice.	Shows how contextually grounded interactions shape the discovery of relevant data insights in precision health in different stages	Empirical - Qualitative	Empirtically shows how collaborative practices embed context in healthcare data through a process model in precision public health.

The second type of methodology employs design science research to develop and evaluate computational interventions that offer theory-informed practical support. While both papers target similar sensemaking challenges, specifically, navigating ambiguity and tailoring insights they do so from different stages of the design cycle, thus offering methodological complementarity, see Table 6.

Tabel 6. Complementarity within design science research studies
This table represents complementarity within design science research studies.

Sense-making Support	**Paper**	**Focus**	**Method-ological orientation**	**Distinct Contribution**	**Comple-mentarity Explanation**
Interpretive Support	**Paper 3**	Explore how tools can be designed to support sensemaking of data in healthcare.	Design science (Theory-driven artifact development)	Develops a IT-artifact that supports sensemaking of multimodal data in mental health.	Focuses on design formulation: identifying requirements and computational framings for nuanced interpretation.
Contextual Fit Support		Context-sensitive theory informed design.		Tailors the dashboard to the specific diagnostic demands of mental health assessment.	
Interpretive Support	**Paper 4**	Shows how sensemaking of data happens using the proposed designed IT-artifact.	Design Science - Quantitative & Qualitative Evaluation	Through evaluating the artifact from Paper 3, it empirically shows the processes of sensemaking of data.	Focuses on design evaluation**:** grounding and tailoring computational interpretive tools for contextual fit through empirical evaluation.
Contextual Fit Support		Empirically validates theory-informed artifact design for sensemaking support.		Empirically evaluates the Paper 3 artifact to support sensemaking for a specific class of problems and to see whether it fits the disease specific needs.	

Paper 3 focuses on the conceptualization and design of an IT artifact for mental health assessment, guided by context-sensitive theory. It contributes primarily to exploratory support by showing how tools can be designed to support sensemaking of data in healthcare through context sensitive theories.

Paper 4 complements this by empirically evaluating the artifact through an experiment by assessing how well the designed IT-artifact supports the sensemaking of data in the context of mental health assessments. Furthermore, the data collected through this evaluation, which was analyzed qualitatively, allows to show the processes of sensemaking of data with the tool.

These two studies provide a theoretically informed design for empirical evaluation addressing both interpretive and contextual fit support challenges from a computational perspective. Their complementarity lies in the way one initiates and theorizes support (Paper 3), while the other validates and refines it (Paper 4), offering a multi-perspective response to the interpretive and contextual challenges posed by ML derived data in mental health settings

Rigor and Relevance

The thesis adopts a multimethod research design that ensures rigor and relevance in contributing to IS, following arguments by leading IS scholars who collectively advocate for research that is both methodologically rigorous and practically useful (Sarker et al. 2025). Following this, the thesis employs multiple research approaches conducted through rigorous investigation while maintaining a clear focus on relevance (Gregor and Hevner 2013; Lee 1999; Lee and Hubona 2009, 2009; Lee et al. 2021; Lyytinen 1999). The thesis incorporates multimethod: quantitative, qualitative, and design-oriented to address complex, real-world problems without compromising scientific rigor (Lee 1999). Recent IS scholarship also highlights that relevance needs to be understood as being pluralistic in nature, considering multiple dimensions such as relevance to different practical stakeholders as well as to academic research through theory development (Lee et al. 2021). Given this, the thesis emphasizes relevance by encompassing multiple dimensions aimed to “elevate and reshape professionals' thinking and actions in a longer perspective” (Lyytinen, 1999, p.26), by proposing various models to support the sensemaking of data, such as conceptual understandings, typologies, process model and designed IT-artifact.

Furthermore, Sarker et al. (2019) suggest the necessity of refocusing on the sociotechnical foundations of the IS field, emphasizing the crucial interplay between technology and people. Ignoring this sociotechnical character risks weakening the discipline's practical impact, as this perspective historically facilitated IS research in addressing relevant real-world issues. These viewpoints guide the present thesis. Consistent with the call for pluralistic and rigorous yet relevant inquiry, this research employs a multi-method design: design science research, qualitative methods, literature reviews, and quantitative methods. Each methodological method was carefully selected to maintain high rigor while addressing significant IS challenges in practice.

Rigor and Relevance in individual papers

The dissertation is comprised of five papers, each representing a distinct genre of IS research. Collectively, these papers illustrate how research can be effectively tailored to address real-world IS problems, thereby generating insights valuable to both academia and practice.

Paper 1 – Literature Review (Typology Development): This paper presents a conceptual-based literature review that proposes a new *typology* in the IS field. The review follows a transparent, rigorous methodology in searching, selecting, and analysing prior empirical IS studies, ensuring academic rigor in the knowledge synthesis. The resulting typology organizes key concepts and findings in the field, contributing to scholarly understanding by clarifying relationships and gaps in literature. At the same time, it has practical relevance as the typology provides practitioners and researchers with a coherent framework to navigate a complex topic. By translating diverse studies into an accessible classification, Paper 1 aims to assist practitioners in identifying which category of solutions apply to their situation of sensemaking of algorithmic intelligence data, thus bridging the gap between academic knowledge and real-world decision-making by providing solutions tailored to their specific contexts (More details about the paper can be found under the 'Paper Summaries' section).

Paper 2 – Literature Review /Etymological (Theorizing Data Knowledge): This paper is a theory-building effort that develops the concept of *"data knowledge"* and its implications. The work is rigorous in its grounding as it builds on an etymological approach going to the root of the word "know" and carefully defines data practice constructs, being consistent with evidence from literature. The theoretical model or framework proposed extends IS theory, contributing to scholarly discourse by integrating previously disparate ideas. Relevance is achieved by focusing on an emergent phenomenon in practice, showing how experts who lack technical skills derive knowledge from data. The paper's concepts help practitioners by illuminating the process through which data is transformed into actionable insight. In this way, a new theorizing on data knowledge not only advances academic knowledge but also offers a lens for non-technical practitioners to better understand and improve sensemaking of data processes in their organizations (More details about the paper are presented under the 'Paper Summaries' section).

Papers 3 and 4 – Design Science Research (DSR) (Mental Health Assessments context): These two papers apply DSR, where an IT artifact was built and evaluated to address needs in the mental health domain. They exemplify the rigor–relevance balance that Hevner et al. (2004) describe as the *"rigor cycle"* and *"relevance cycle"* of DSR. On the rigor side, the development of the artifacts followed established DSR guidelines and theory (Abbasi et al. 2024). The design of the IT-artifact was grounded in prior scientific knowledge (e.g. informing the design principles on prior proven frameworks: integrative sensemaking theory, signal detection theory and concepts derived from the psychology literature), and the artifact was evaluated using user experiments with 150 participants (Paper 4) to demonstrate its efficacy. Each of the participants was given 3 tasks, which resulted with 450 evaluations of the proposed IT-artifact. From a computational design perspective, the evaluation employed a set of design validity measures that support the proposed design theory (Abbasi et al. 2024; Rai et al. 2017). Specifically, the evaluation of the IT-artifact, includes a measurement linking users' attention patterns to integrative note-taking behaviours during sensemaking, and further to task-level performance outcomes, including accuracy, confidence, and time. This evaluation provided evidence of the artifact supporting sensemaking of data in the context of mental health assessments. The robustness of the experimental design further strengthens the validity of these findings. The experimental design evolved through an iterative and progressively refined process. The evaluation began with a pilot study, which informed key decisions regarding tutorial provided to participants, task timing, interface clarity, and procedural refinements prior to the main study. Building on this foundation, participants in the main experiment were randomly assigned and evenly distributed across experimental conditions to reduce selection bias and ensure comparability between settings. The experimental tasks themselves were grounded in established practices reported in the mental health assessment literature, resulting in clinically related tasks centered on detection of depression and integrative notetaking to capture patterns of sensemaking. As the evaluation progressed, a multi method approach was adopted, combining quantitative measures of performance and interaction with qualitative analyses of note-taking behaviours during sensemaking. This combination enabled triangulation across multiple forms of evidence and strengthened confidence in the robustness and interpretability of the findings. Moreover, by engaging practitioners throughout evaluation, these studies ensured the findings do not simply extend on existing theory but also can be practically usable in mental health sensemaking of data. This resonates strongly with the IS calls on DSR to build and rigorously test IT artifacts (Abbasi et al. 2024; Karahanna et al. 2006; Rai et al. 2017). (More details about the papers are presented under the 'Paper Summaries' section).

Paper 5 – Qualitative Study (Precision Public Health context): This paper uses qualitative research (semi-structured interviews) to investigate an IS question in the context of *precision health*. The research design emphasizes qualitative rigor by employing systematic coding processes and providing detailed nuances of collaborative sensemaking through a process-model to enhance the trustworthiness and validity of the findings. The practical relevance arises directly from the study's focus on precision public health which is a practice area in healthcare where sensemaking of data happens through technology and group of diverse healthcare practitioners in collaboration with technical experts which are used to tailor healthcare to specific group of populations or diseases. By studying precision public health, a context-sensitive setting where it requires a tailored understanding of data in line with Lee's (1999) and Lyytinen's (1999) suggestions, this qualitative research derives lessons from real-world experiences, ensuring that theory is informed by practice and can in turn inform practice in a cycle of learning (More details about the paper are presented under the 'Paper Summaries' section).

Ethical considerations

As mentioned previously, this thesis applies a multi-method approach that combines Design Science Research (DSR), experimental evaluation, and qualitative interviews with diverse healthcare practitioners and other stakeholders. Ethical considerations were integrated throughout the research process: from study design and recruitment to data handling, analysis, and reporting with attention to the professional settings in which participants work and the cross-national context of data collection.

Ethical oversight, research context, and study framing

Given that data collection was conducted in different national contexts, ethical oversight was sought in relation to where each study took place. The DSR experimental studies (pilot and full experiment) involved participant recruitment and data collection in the United States and were reviewed and approved by the University of Notre Dame Institutional Review Board (IRB), protocol ID 25-03-9149. Prior to this, an ethical advisory opinion was requested in Sweden to assess whether a formal Swedish ethical application was required for the planned study activities where the project was explained in detail. The advisory opinion concluded that a formal Swedish application was not necessary. Furthermore, the qualitative interview study focused on collaborative sensemaking and multi-level stakeholder perspectives in precision public health was conducted in Sweden and was handled in accordance with Swedish ethical guidelines for research involving human participants, including informed consent, confidentiality, and responsible storage and reporting of interview materials.

The application domains of this thesis include mental health assessment and precision public health. However, the studies do not involve clinical interventions, patient recruitment, or collection of participants' personal health information. The experimental work evaluated a research prototype dashboard using standardized research stimuli, and the qualitative study focused on professional perspectives and work practices.

Data sources, consent, and confidentiality

The DSR project used pre-existing, de-identified secondary research data to construct the dashboard. The dashboard visualizes features derived from the DAIC-WOZ dataset, part of the Distress Analysis Interview Corpus (DAIC) (Gratch et al. n.d.). Access was obtained through a formal request and approval process, and the research team signed and adhered to the data use agreement. The shared version of the dataset used in this thesis contains no personally identifiable information. In addition, DAIC-WOZ dataset does not include any raw video, so the facial information is provided only as automatically extracted numerical Action Units (AUs), representing muscle activations in facial coordinates. The dashboard therefore visualized derived, non-identifiable signals (e.g., numerical Aus).

For the evaluation of the design science study, participants were recruited via the Prolific platform and provided electronic informed consent prior to participation, including the right to withdraw at any time without penalty.

Participants who did not provide consent were not allowed to proceed. For the qualitative interviews, informed consent was obtained prior to participation, including information about interview procedures, recording (where applicable), intended use of the material, and the right to pause, skip questions, or withdraw.

Confidentiality was protected through anonymization and secure storage practices. For the experimental studies, task responses (classifications, written summaries/justifications, survey responses) and interaction measures (e.g., clicks and mouse movements) were stored under randomized study IDs, with no identifying information embedded in the research dataset. No audio or video recordings of participants were collected.

For interviews, zoom recordings and transcripts were stored securely, pseudonymized during transcription, and stripped of identifying details where only anonymized excerpts are included in the thesis and publications.

Participant burden, artifact responsibility, and researcher reflexivity

The expected burdens and risks to participants were limited. In the experimental studies for the DSR project, potential burdens included mild cognitive fatigue due to session length (around one hour) for note-taking and assessments tasks. These were mitigated through clear instructions, tutorial support, the ability to discontinue participation at any time, and framing that emphasized the study's focus on evaluating dashboard features rather than judging participants. The pilot study also served to refine task clarity and reduce unnecessary burden before conducting the full experiment. For interviews, burden primarily involved time and the possibility of discussing organizational challenges where participants were reminded that they could skip questions or stop at any point.

The artifact design and evaluation were approached as socio-technical work, where interface choices can influence interpretation and confidence. The data from DAIC-WOZ dataset, included ML generated modalities such as speech to text, or ML driven facial activations. To support responsible interaction with algorithmic components, the proposed IT-artifact includes ML scores (e.g., predictive indicators and confidence information). Furthermore, given that this was an online experiment, in the tutorials I provided the participants explanation of the dashboard components with recording my voice and figures where I further displayed concrete examples of task handling. Moreover, in developing the artifact, informal conversations with practitioners were used to remain attentive to practical needs, terminology, and constraints. These interactions were not treated as formal data collection, were not recorded, and were used as contextual input to inform design decisions and improve relevance without adding participant burden. On the other side, before interviewing the participants for understanding the collaborative sensemaking of data, we had informal conversations with the head of precision public health projects in one of the regions in Sweden. This helped me understand the nuances of precision public health context in Sweden, the ongoing projects and the technologies being used. Furthermore, during the qualitative data collection, I contacted some of the participants again, in order to raise some deeper questions regarding their sensemaking of data. This helped me address unclarified parts and getting to know more about their sensemaking during the research process.

Finally, prior to applying for IRB approval in the United States, I completed a formal ethics training course required for conducting human-subjects research. This training informed both the preparation of the IRB application and the practical implementation of consent, design process, confidentiality, and risk-mitigation procedures.

Methods applied in the individual papers

Paper 1: Literature Review – Concept-based analysis

This paper conducted a structured literature review using the Scopus database to identify peer-reviewed empirical articles on human-AI collaboration. The review focused on work published over the past ten years, as this period saw the majority of empirical studies on the topic. Only articles written in English were included, and the search was conducted with a global scope.

The initial selection was based on title and abstract screening to ensure relevance to the research topic. Two authors jointly selected the articles for inclusion, and two additional authors verified the selection to ensure accuracy and quality control.

The review was structured following the concept-based approach outlined by Webster and Watson (2002). A directed content analysis method (Hsieh & Shannon 2005) was applied to categorize the studies. Articles were first classified based on the type of Human-AI collaboration. Key concepts related to narrative responsibility were then extracted and grouped into thematic categories. These themes provided the foundation for developing a new typology, which will be discussed later in the findings chapter.

The proposed typology (Ademaj, Chowdhury, et al. 2025) was created through a combination of substruction (adding dimensions for completeness) and reduction (removing overlaps for simplicity), following Nickerson et al. (2013). The typology was grounded in Coeckelbergh's (2023) framework and evaluated on four criteria: inclusion, distinction, equivalence, and granularity (Ademaj, Chowdhury, et al. 2025). Each cell of the typology was illustrated with examples drawn from the literature, demonstrating its relevance across domains such as healthcare and strategic decision-making.

To strengthen the theoretical foundation, the paper adopted Cornelissen's (2017) guidance by introducing novel concepts, clarifying how their interactions generate new insights, offering directions for future research, and providing an illustrative application of the typology in AI-based decision contexts.

Paper 2: Literature Review – An etymological approach on getting to the root of the word "know"

The paper conducted a systematic literature review (SLR) to explore how data knowledge is conceptualized within organizational contexts, particularly beyond the role of data scientists. Using Scopus, articles were selected from AIS Senior Scholars' Basket journals, covering the period from 2000 to 2023.

An inductive approach guided the analysis of the data, involving iterative coding to identify initial sub-concepts. These sub-concepts were then categorized using an etymological approach that traced the linguistic origins of the term knowledge. Drawing from etymological dictionaries, the paper identified five core dimensions: "to know, perceive, acknowledge, declare, and recognize" (Koukouvinou et al. 2023, p.5) (later merged with perceive). These dimensions were then combined with the concepts from the inductive analysis of the selected empirical studies which led to derive a more grounded understanding of what it means to know data.

Paper 3 and Paper 4: A Design Science Research methodology

Design Science Research in IS: Foundations, evolution, and relevance for this thesis

DSR is one of the foundational methodologies in the IS discipline. Its primary aim is to develop and evaluate artefacts such as models, methods, systems, or technologies that address real-world problems while contributing to theoretical knowledge (Gregor et al. 2020). Early work by Walls et al. (1992) introduced the concept of an information systems design theory and proposed that prescriptive knowledge could be structured through goals, constructs, and testable propositions. Building on this, March and Smith (1995) drew a distinction between the natural sciences, which focus on explaining phenomena, and design science, which focuses on creating purposeful artefacts. Their research centered on artifact design and evaluation within IS.

In the 2000s, efforts to clarify how DSR should be conducted began to take shape. Hevner et al. (2004) proposed seven guidelines for rigorous and relevant design research, including the need for clear problem relevance, artefact novelty, thorough evaluation, and effective communication of contributions. Peffers et al. (2007) followed with a six-step process model that provided a practical framework for conducting DSR, from problem identification to dissemination. Gregor et al. (2007) expanded this discussion by focusing on the structure of the knowledge produced. They argued that a full design theory should specify the purpose of the artefact, its theoretical foundation, design principles, and propositions that can be tested.

One important early effort to bring socio-technical thinking into DSR is Carlsson's et al. (2011) work on “Socio-technical IS Design Science Research.” They argue that effective design research must address not only technical artefacts but also the organizational and governance processes that surround them. They propose a four-step research cycle: (1) identify the problem and desired outcomes, (2) review theories and evidence, (3) propose or refine design theory, and (4) test it in practice, not only in terms of system functionality but also in how it supports managerial routines and roles. Their proposed framework anticipates later work on the importance of socio-technical balance and aligns closely with Sarker et al.’s (2019) concept of the socio-technical axis of cohesion, which emphasizes that meaningful IS artefacts emerge from the coordination of structure, human agency, and technical systems.

As DSR matured, new methodological variants emerged. Action Design Research (Sein et al. 2011) combined artefact creation with real-world organizational intervention, emphasizing that design and context evolve together. These developments strengthened the understanding that effective IT artefacts arise only when social and technical aspects are cohesively integrated, a view captured in Sarker et al.’s (2019) concept of the socio-technical axis of cohesion.

More recently, scholars have deepened the socio-technical perspective by examining how artefacts derive their meaning and effectiveness from the practices in which they are embedded. Gregor et al. (2020) argue that digital artefacts should be studied not as standalone technical objects, but in relation to the professional and organizational practices in which they are used. Their work demonstrates that the meaning, value, and effects of artefacts emerge through use and interpretation in specific situations. This perspective shifts the focus from what an artefact does to how it is used within everyday work routines and professional sensemaking processes. Gregor et al. (2020) approach aligns closely with socio-technical design science by emphasizing that artefacts interact dynamically with routines, responsibilities, and interpretive practices over time. From this perspective, evaluation extends beyond technical performance to consider how well an artefact fits with existing work practices, supports professional judgment, and enables meaningful engagement with information. This view is particularly relevant in domains like healthcare, where the same data visualization or decision support tool may be interpreted and used differently depending on clinical context, professional expertise, and organizational norms.

Parallel to these socio-technical developments, the scope of DSR has expanded to include what has been termed computational design science. This branch focuses on building artefacts such as ML models, decision algorithms, and data-processing pipelines. Rai et al. (2017) described this as a new DSR genre characterized by the development of computational artefacts and their evaluation using benchmark datasets, code transparency, and performance metrics. Abbasi et al. (2024) extend this thinking by proposing publishing pathways for DSR on AI, emphasizing the importance of practice in DSR, explainability, transparent data practices, and linking algorithmic artefacts to human contexts. More specifically, the increasing volume and complexity of data, together with AI-based data processing and predictions, fundamentally change the nature of design problems (Abbasi et al. 2024). Rather than addressing a clearly defined problem space, design research must often first conceptualize the problem so that it can be meaningfully formulated and supported by solutions. As highlighted by Abbasi (2024), this shift is especially relevant in AI-enabled contexts, where understanding the problem is at least half the battle or "a key contribution is the conceptualization itself" (Gregor and Hevner 2013, p. 346)" (p. 448). In the context of healthcare, this study treats the conceptualization of sensemaking of complex data as a necessary design step for developing solutions based on ML-inferred cues.

At the same time, the field has revisited the issue of practical relevance. Lee et al. (2021) argue that much behavioral IS research only reaffirms well-known concepts and lacks meaningful impact. They suggest that DSR, along with more ambitious theoretical exploration, is needed to produce contributions that are both innovative and consequential. This position aligns with the socio-technical axis of cohesion, which stresses that IS artefacts should be evaluated not only by their technical performance but also by how well they align with human routines and organizational goals.

This thesis is situated within this evolving DSR tradition. It contributes to both traditional and computational branches of DSR by designing and evaluating an IT-artefact that support the context-sensitive sensemaking of data in healthcare. Specifically, it connects two key strands of design research: the use of data as a tool and the growing role of algorithmic systems. On one hand, it builds an IT-artefact, a visual analytics dashboard which is informed by context sensitive theories of sensemaking, signal detection and psychology that help healthcare practitioners engage with data meaningfully and support their sensemaking. On the other, it explores how data processed by intelligent systems, like AI-based diagnostic tools can be designed to support the sensemaking of healthcare practitioners. Drawing on the practice-oriented perspective of design science (Abbasi et al. 2024; Gregor et al. 2020; Rai et al. 2017), this thesis recognizes that the value of these artefacts is not determined solely by their technical capabilities but emerges through their integration into clinical routines and professional interpretation. The design and evaluation processes therefore attend not only to system functionality and algorithmic performance but also to how artefacts are used within specific healthcare contexts (Karahanna et al. 2006). By drawing on these perspectives, the thesis demonstrates how design science can support complex, context-sensitive sensemaking processes in domains where data is not just an input to decisions, but a socio-technical actor that must be interpreted computationally in order to support sensemaking of data. By doing so, the work answers Abbasi's et al. (2024) call to make computational design research both technically rigorous and contextually grounded.

Paper 3- Design instantiation - Design of a Dashboard for supporting multimodal sensemaking of data in healthcare

This paper adopts a DSR methodology to propose a conceptual design and instantiate an IT artifact intended to support clinicians' interpretive sensemaking of multimodal patient data in mental health contexts. The design process follows Walls et al. (1992), which structures the development of design knowledge into kernel theories, meta-requirements, meta-design, and testable hypotheses.

The kernel theories informing the design include Integrative Sensemaking Theory (IST) and Signal Detection Theory (SDT), which were extended with additional concepts from the clinical psychology literature to better accommodate the unique contextual needs of mental health assessments. These theoretical foundations guided the derivation of meta-requirements, the functional and non-functional needs the artifact must fulfill and informed the meta-design features of the dashboard.

The artifact instantiated in Paper 3: a multi-modal mental health dashboard is designed using data derived from the Distress Analysis Interview Corpus (DAIC-WOZ Database)[1], a widely recognized dataset in mental health research (Gratch et al. n.d.; Ringeval et al. 2019). The DAIC dataset contains recordings of remote clinical interviews, designed to support the diagnosis of different mental health conditions. From these interviews, a range of multimodal data in the form of behavioral, vocal, and textual data streams are extracted using ML models. Specifically, the dashboard uses ML-derived features across three key modalities: textual cues (e.g., emotional sentiment), vocal characteristics (e.g., pitch variation), and facial expressions (e.g., muscle activations). While the facial expression and vocal characteristics were derived as features from the DAIC dataset, for textual cues I have grouped the interview transcripts into emotional sentiments using a lexicon dictionary, LIWC [2].

While the paper details the design instantiation of a prototype dashboard (see Chapter 4 -Paper 3), including how each feature maps to the underlying theory and requirements, the empirical evaluation of the artifact was not conducted within the scope of this paper. Instead, the experimental setting was proposed, which served as evaluation in Paper 4. The contribution of this study is thus the design theory and artifact instantiation, providing a theoretically grounded and context-sensitive basis for future empirical assessment.

Paper 4: Evaluation of a Multimodal Dashboard for Mental Health Assessments

This paper presents the evaluation phase of a DSR project through a user experiment aimed to evaluate how well a proposed digital dashboard helps healthcare professionals interpret multimodal data such as facial muscles activated, tone of voice, and text patterns that may indicate depression.

The experimental materials were drawn from the DAIC-WOZ dataset, which includes annotated interviews classified by depression severity. A

[1] https://dcapswoz.ict.usc.edu/

[2] https://www.liwc.app/dictionaries

between-subjects design involved 150 professionals recruited from Prolific, and were randomly assigned to one of three conditions: a full-featured dashboard, a baseline interface, and a non-ML dashboard with certain features removed for assessment. The participants were given to take notes and asses the depression. They also filled a post-task survey about the dashboard's usefulness and ease of use, while click and mouse movement data were collected for understanding sensemaking processes in mental health assessment.

The IT-artifact's effectiveness in supporting sensemaking was evaluated through both quantitative and qualitative methods, checking detection accuracy against ground truth labels and assessing its support for depression confidence. The note-taking part which was purposely designed to test its support on sensemaking was qualitatively analyzed, whereas the post-task surveys evaluated perceived usefulness and ease of use of the dashboard components. More details about the evaluation design can be found in the next (Chapter 4- Paper 4).

This evaluation provides empirical evidence on how well the dashboard supports interpretive sensemaking in context-sensitive healthcare contexts as mental health.

Paper 5: Data collection and analysis - Qualitative Analysis

To explore the sensemaking of data when data is understood as practice, we have used the context of precision health on a population level. The precision health on population level consists of diverse domain experts who deal with data selection and analysis on group level. Group level analysis in precision health consist of data about a particular group of patients with a specific diagnose or for example focusing on a specific drug. The data that is being used in such context is diverse which includes clinical data, data from national registers and other types of data such as environmental or genetic data.

The empirical work for this study was conducted within precision public health projects in Sweden. A qualitative approach, conducting 26 semi-structured interviews was adopted to explore how collaborative data sensemaking is carried out in practice. The interviews were conducted with a diverse group of experts, including biostatisticians, clinicians and other diverse healthcare professionals such as geneticists, immunologists, epidemiologists, and data integration professionals on regional levels of Sweden.

To begin the research process, we have started with informal conversations with the head of precision public health initiatives in one of the Sweden's Regions. This approach allowed us to be familiar with the context, the ongoing projects and it helped with the inclusion of a rich variety of perspectives from both technical and clinical domains. All interviews were conducted online via Zoom, lasting approximately one hour each, and were audio-recorded and transcribed.

The data analysis proceeded in two iterative phases. In the first phase, an inductive data-driven approach was used to break down the sensemaking process into distinct collaborative stages, following Pentland's (1992) recommendation to analyze such processes in component units. Interview data was coded inductively, with a focus on tracing interactions and interpretive actions between technical and clinical stakeholders. This allowed the identification of triggers, actions, and contextual factors shaping each phase of collaborative data interpretation.

As the analysis progressed, the emerging findings were examined in relation to relevant theoretical literature. While early analytical framing drew on process-oriented perspectives on sensemaking, the empirical material consistently highlighted the role of experience-based judgment in collaborative interpretation. This led to the use of practical wisdom (phronesis) as an analytical lens to deepen the understanding of how collaborative sensemaking of data unfolds in practice.

Paper Summaries

This section introduces the papers that comprise the thesis. Table 7 summarizes each paper in terms of empirical material, analytical approach, and my role as an author. The overview is intended to clarify how the papers differ in data collection material and method while contributing to the thesis as a whole. In addition, each paper summary explains how the paper addresses the thesis research question and contributes to the two dimensions of sensemaking support examined in this thesis: interpretive support and contextual fit support.

Tabel 7. Paper summaries

This table represents Paper 1-5 summaries. *Multiple authors were involved in these activities.

Paper	Material	Analytical approach	Author's role
1	28 published articles -empirical research of human-AI collaboration.	Concept-based review.	First author Literature search* , conceptualization *, writing *, editing *
2	34 published articles that focused on data work within different types of business organizations while trying to emphasize non-technical employees.	Etymological approach Systematic Literature Review	Second author Literature search*, analysis, conceptualization*, writing *, editing *
3	Multimodal and multi-model data from the DAIC-WOZ database[3] which contains clinical remote interviews with 30 depressed and 30 non-depressed individuals.	Design science research Textual data: I have classified the interview transcripts into emotional sentiments using a lexicon dictionary, LIWC.	First author Literature search, problem identification, conceptualization *, informing meta-requirements and meta-design *, tool implementation and design, experiment design *, writing, editing.

[3] https://dcapswoz.ict.usc.edu/

Paper	Material	Analytical approach	Author's role
4	Experiment design with 150 practitioners x 3 tasks in Prolific (healthcare practitioners: nurses, medical staff, psychology students, social workers). 450 evaluations of the proposed IT-artifact: -Depression detection binary classification - Indication of depression levels - Ratings of participants' self confidence in using the IT-artifact -Note-taking summaries -Post-task survey on usefulness, ease of use and future use for each component of the IT-artifact -Ranking of IT-artifact components based on usefulness and ease of use -Number of clikcs and mouse movements of participants interacting with the dashboards of the three settings	Design science research Quantitative Analysis on task accuracy, depression indication confidence, self-confidence levels, note-taking cue depth for sensemaking Qualitative Analysis on note-taking	First author Literature search, problem identification*, conceptualization*, informing meta-requirements and meta-design *, tool design*, experiment design, evaluation through quantitative methods and qualitative methods*, writing *, editing *.
5	26 semi-structured interviews with biostatisticians and health experts of different backgrounds	Qualitative analysis	First author Literature search, data collection and analysis, conceptualization *, process model proposition, writing, editing.

Paper 1

Ademaj, G., Chowdhury, A., Sarker, S., & Keller, C. (2025). The role of narrative responsibility within Hybrid Intelligence.

In this paper, let us shift the focus to data as a algorithmic intelligence. In this paper, we examine the emerging concept of hybrid intelligence (HI), the collaboration between humans and AI through the lens of data as algorithmic intelligence, one of the three data roles that guide this dissertation. This paper addresses how AI and human actors collaboratively make sense of data in complex organizational environments. Motivated by the growing presence of AI in decision-making, particularly in data-intensive sectors like healthcare, the study explores the interpretive dimension of this collaboration. The introduction frames the problem by showing how AI is no longer a passive computational tool but an active agent shaping how humans interpret and act on data. This shift gives rise to new interpretive responsibilities that are not well addressed in current IS literature.

The paper situates its investigation within the concept of Hybrid Intelligence (HI), a mode of collaboration where human and AI intelligence are combined to solve complex problems. While HI has been studied in relation to decision-making and task performance, this paper brings attention to its interpretive implications, especially how sensemaking unfolds when AI is not just aiding humans but also influencing their understanding. Drawing from Coeckelbergh's (2023) concept of Narrative Responsibility (NR), the study argues that humans are responsible not only for making decisions but for creating, evaluating, and adapting the narratives that emerge from AI outputs. However, the paper (Ademaj, Chowdhury, et al. 2025) extends this concept by emphasizing that AI also participates in shaping these narratives, thereby shifting our understanding of responsibility in human-AI collaborations.

To investigate this, the paper conducts a concept-based literature review using a structured search of peer-reviewed studies in the Scopus database. The study identifies four recurring patterns of how narrative responsibility is enacted, (Ademaj, Chowdhury, et al., 2025, p.5):

1) "Narrative Synchronicity": how humans and AI align in task understanding and context awareness.
2) "Compulsive Narrative Reasoning": how AI outputs trigger iterative reasoning by human actors.

3) “Adaptive Narrative Adjustments”: how both human and AI contributions are adjusted in response to new data or contextual shifts.
4) “Continuous Narratives”: how interpretation evolves over time through repeated engagements with AI outputs.

The paper proposes a typology that maps these four dimensions across the three forms of HI, showing how interpretive responsibilities are distributed, enacted, and sometimes challenged in different configurations of human-AI collaboration, see Figure 2. Importantly, the typology highlights that sensemaking is not linear or controlled solely by humans. Instead, it is a co-constructed process, shaped by the dynamic interaction between algorithmic insights and human judgment, a notion captured in the paper through the lens of AI-in-the-loop.

The typology was evaluated using four established criteria for typology quality: inclusion, distinction, equivalence, and granularity. Each of the 12 matrix cells, representing the intersection of narrative responsibility dimensions and hybrid intelligence forms was populated with empirical examples from the literature, ensuring coverage (inclusion). The dimensions were shown to be conceptually distinct with minimal overlap (distinction), positioned at the same level of abstraction (equivalence), and generalizable across domains like healthcare and strategy while offering sector-specific relevance (granularity).

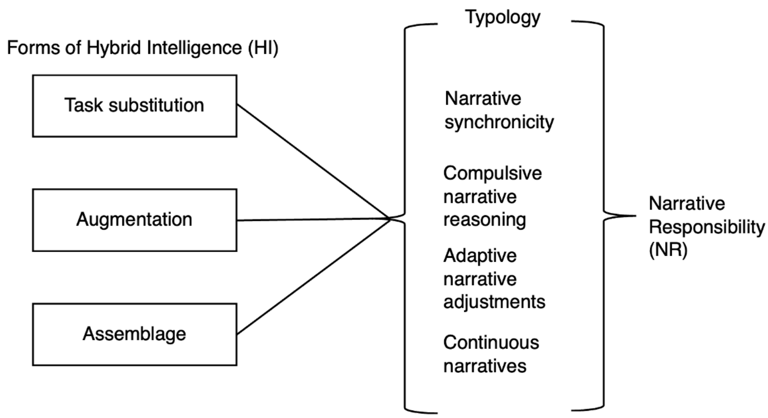

Figure 2 “Typology of NR in hybrid intelligence” (Ademaj, Chowdhury, et al., 2025, p.5).

Furthermore, to show the practical usefulness of the typology, it was applied to the empirical findings of a case involving AI-assisted medical diagnosis by Jussupow et al. (2021). The comparison looked at how clinicians responded when they either accepted or questioned AI recommendations. When clinicians thoughtfully engaged with the AI outputs building their own explanations, evaluating carefully, and reflecting over time, the typology's dimensions of synchronicity, compulsive reasoning, and continuous narratives were clearly observed (Ademaj, Chowdhury, et al. 2025). In contrast, when AI was either ignored or accepted without reflection, important aspects of narrative responsibility were missing. Actions like dismissing AI errors or justifying poor decisions showed a lack of adaptive adjustment (Ademaj, Chowdhury, et al. 2025). These patterns demonstrate that the typology helps identify both responsible and problematic human-AI interactions, providing insight into how clinicians think and act alongside intelligent systems.

By showing how the responsibility in narrative between humans and AI-generated insights manifests across different forms, the paper offers a strong conceptual basis for interpretive support of sensemaking in fields like healthcare. It points to key design strategies such as creating deliberate reflection points, matching user skills with tasks, and enabling two-way feedback that can help ensure that AI tools support thoughtful, ethical, and context-aware use of data. Furthermore, the nuances on the different forms of human-AI collaborations advances the contextual fit support of sensemaking.

Hence, this paper contributes to the thesis's overarching research question: *"How to support the sensemaking of data in healthcare"* by offering a typology that attends to the responsible narrative dimensions of human-AI interaction. It suggests that meaningful support for sensemaking must account for how AI not only offers data outputs but actively participates in shaping the way data is understood, especially in sensitive domains like healthcare. Furthermore, the proposed typology provides a basis for evaluating and designing systems that balance machine-driven insights with human values, contextual understanding, and ethical reflection.

Paper 2

Koukouvinou, P., Ademaj, G., Sarker, S., & Holmström, J. (2023). Ghost in the Machine: Theorizing data knowledge in the Age of Intelligent Technologies.

In this paper, let us shift the focus to data as practice, asking what it means getting to know data when AI is woven into everyday work. We argue that in context-sensitive settings, data does not arrive as a neutral input waiting to be processed. Instead, knowing data is a socio-technical, situated, and narratively constructed process. In this paper, we develop a conceptual model of “data knowledge” built around four interrelated practices. The four practices are unformed from an etymological approach, by exploring the root of the word “know”, see Figure 3.

Dimension of the Verb	Dictionary Meaning	Elaborating the relations	Sub-concepts	Main concepts	Relevant Articles
To Know	-“To be acquainted or familiar with.” -“To have experience with.” -“To have understanding of.”	Employees´aacts of getting familiar with data and their expertise. Getting to know the data.	Data capturing Data curation Contextualing Data discovery Data sourcing Data use Identification Re-organize and map	Unveiling Data	Boldosova (2019);Grover et al.,(2018);Mikalsen and Monteiro(2021); Parmiggianni et al., (2022);Sternkopf and Mueller,(2018);Saghafi et al.,(2022); Tamm et al., (2022).
To perceive	-“The ability to see, hear, or become aware of something through the senses: cognition; understanding.”	Cognite outputs of both data and the surrounding environment.	Data-centric knowing Managing data cognitive of data Interpreting data outputs Contextual enablers Data understanding Pro-activeness	Balancing between data and cognition	Aaltonen et al., (2021); Grover et al. (2018); Mikalsen and Monteiro(2021); Sternkopf and Mueller,(2018); Tamm et al., (2022).
To acknowlegde	-“Accept or admit the existance or truth of.” -“To disclose knowledge of or agreement with.” -“To notice.”	Acknowledge occuring in multiple levels including: the organizational capabilities (e.g., readiness, resources, and negotiations)leading to agreements on data management and collaboration. It refers to acknowledging the competive pressure, and the data proccessed.	Organizational capabilities Individual absorptive capacity Negotiation Cross-department Collaboration Technological capability Environmental dynamism Reproposed data Re-used data	Acknowledging external and internal capabilities	Aaltonen et al., (2021); Aaen et al., (2022); Boldosova (2019);Chen et al., (2015);Mikalef and Krogstie (2020); Shao et al., (2022); Tamm et al., (2022).
To declare	-“To make known formally, officially or explicitly.”	All aspects of data communication and understanding.	Data sharing Deliberate storytelling Multi-perspective storytelling (Situated) data interpretion Flexibility in data representation	Realizing Data	Aaen et al., (2022); Almklov et al., (2014); Boldosova (2019); Mikalsen and Monteiro(2021); Sternkopf and Mueller,(2018);Park and Mithas (2020); Tamm et al., (2022);Someh et al., (2023)

Figure 3 An etymological approach of knowing what it means to know data
“Visual Representation of the etymological meaning, and conceptualization of each category and its elements” (Koukouvinou et al., 2023, p.6).

First, unveiling data describes the effort of sourcing, preparing, and reorganizing raw inputs so that AI outputs become visible and legible in clinical workflows (Koukouvinou et al., 2023). Second, balancing data and intuition captures the tension practitioners face when AI signals clash with embodied expertise (Koukouvinou et al., 2023). Third, acknowledging capabilities reminds us that data knowledge depends on whose voices are invited into the interpretation (Koukouvinou et al., 2023). Finally, realizing data highlights the storytelling and communication work through which data transforms into actionable insight (Koukouvinou et al., 2023).

Paper 2 responds to the thesis's research question: *"How to support sensemaking of data in healthcare?*" by developing the concept of data knowledge to provide interpretive support for practitioners who need to engage with data in practice but do lack technical expertise. It does so by clarifying what constitutes data knowledge and how it is enacted. This theoretical unpacking enables practitioners and systems to better support meaning-making where data is not just read or analyzed, but actively "known" through practices like interpretation, balancing intuition, and context-sensitive expertise. The paper offers conceptual clarity that helps healthcare actors become aware of how interpretive efforts are shaped, not just by data itself, but by how they come to "know" data.

In the context of healthcare, sensemaking of data increasingly depends on practitioners' ability not just to access or analyze data, but to interpret it meaningfully. This is especially needed in healthcare, as most of the time the healthcare practitioners do lack technical knowledge. This paper addresses the critical need to clarify what it means to "know" data by non-technical experts by introducing data knowledge as a novel construct that captures how organizational actors make data intelligible through processes like unveiling, interpreting, and acknowledging contextual capabilities. Specifically, it develops the construct of data knowledge to capture the interpretive dimensions of working with data, going beyond existing terms like data literacy or data sensemaking. While data literacy focuses on capabilities and sensemaking on interpretation, data knowledge synthesizes them to address how data becomes meaningful through interaction, context, and shared understanding (Koukouvinou et al., 2023).

Paper 3

Ademaj, G, Zhang X, Abbasi, A, Sarker, S, Sarker, S. (2025). Designing Support for Sensemaking in Multimodal, Multi-model Mental Health Assessments.

In this paper, let us shift the focus to data as a tool and algorithmic intelligence. This paper addresses the challenge of supporting the sensemaking of data in complex multimodal and multi-model environments by designing a computational IT-artifact tailored to mental health assessments. The study follows the DSR and responds to the growing need for tools that help mental health practitioners make sense of data that are algorithmically generated and multimodal in nature. Specifically, the paper focuses on mental health assessment contexts where large volumes of data such as text, audio, and video are increasingly processed through remote interviews and processed through diverse ML models, see Figure 4.

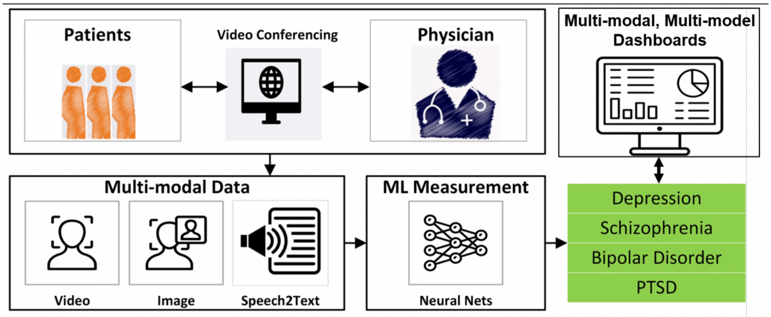

Figure 4 The context of multimodal data in remote mental assessments
"Overview of System Design for Multi-modal, Multi-model Dashboard" **(Ademaj et al., 2025, p.2).**

To support mental health practitioners' sensemaking, this study proposes and implements a multi-modal, multi-model dashboard that integrates design insights from Integrative Sensemaking Theory (IST) and Signal Detection Theory (SDT). These theories are deliberately chosen for their applicability in context-sensitive domains like healthcare, where clinical decisions rely heavily on interpreting nuanced behaviors. Five key design elements derived from these theories guide the artifact's development (Ademaj, Zhang, et al. 2025): (1) should support the user with access to raw, unprocessed cues, (2) should support the user with identification of systematic fluctuations of behaviors over time, (3) should support the user with recognition of consistent behavioral cues over time, (4) should support the user with access to ML model performance, and (5) should support the user with exploration of data at multiple granularities. These design requirements served to guide the design of the IT artifact, the dashboard to help mental health practitioners engage with the data actively and reflectively, rather than relying passively on algorithmic outputs, see Figure 5.

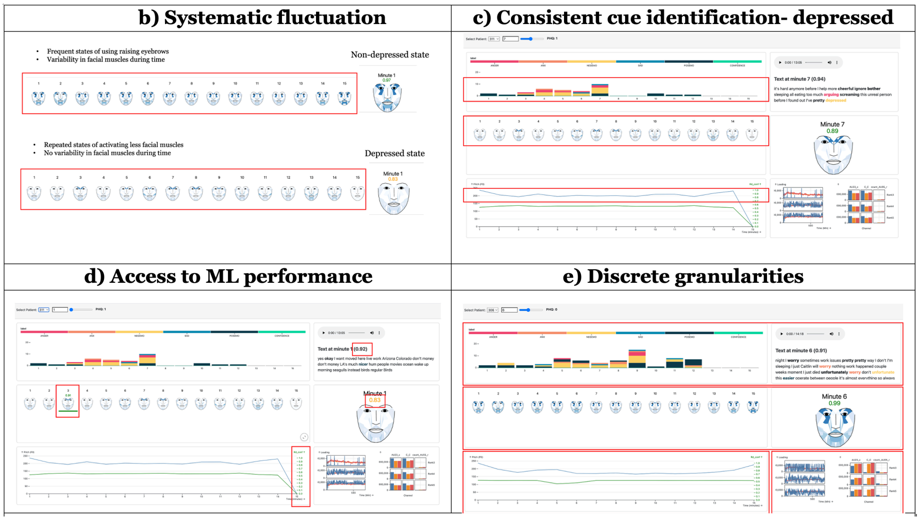

Figure 5 Dashboard artifact and the manifestation of data cues across modalities and time
“Dashboard functionality screenshots” (Ademaj et al., 2025, p.6).

To assess the effectiveness of the proposed dashboard, this paper proposes a design experiment for evaluating the tool that is run in Paper 4. The evaluation plan involves a between-subjects user experiment, designed to understand how well the tool supports sensemaking of data through note-taking on specific aspects of behaviors from the dashboard, and by asking to detect whether the person is depressed or not. The study uses ablation testing to isolate the contribution of individual design elements. While this paper focuses on the artifact’s design and theoretical grounding, the evaluation was conducted in Paper 4.

By designing and demonstrating a tool that helps distinguish signal from noise and supports healthcare practitioners sensemaking in algorithmically mediated contexts, the paper contributes directly to the thesis’s overall research question: *“How to support sensemaking of data in healthcare?”* It does so by focusing on the lens of data as algorithmic intelligence and data as a tool, offering concrete design requirements for how healthcare tools can arrange and visualize data in ways that are contextual to the disease context and hence enhance healthcare decision-making.

By embedding computational interpretive support within a dashboard that is contextually tailored to the needs of mental health context, the paper offers a dual contribution to the research question. First, it provides interpretive support by showing the design of the tool aimed to support sensemaking of data for mental health practitioners. Second, it ensures contextual fit support by grounding the dashboard's design in theories (IST and SDT) and psychology literature that match the unique interpretive demands of mental health assessment. In doing so, the paper exemplifies how theory-informed, domain-specific design aims to support sensemaking in algorithmically mediated healthcare settings.

Paper 4

Ademaj, G, Zhang, X, Cai J., Sarker, S, Sarker, S., Abbasi, A. Sensemaking in Multimodal, Multi-model Environments: Designing Support for Remote Mental Health Assessments

This paper builds on the design artifact proposed in Paper 3 by evaluating whether it supports sensemaking in remote mental health assessments. The design requirements and most design elements are retained, but the artefact is refined in two ways. First, it incorporates an overall AI-based depression prediction component. Second, it frames sensemaking in multimodal and multi-model environments as a design problem by theorizing how ML-processed data signals interact across time and across levels of detail. The paper therefore evaluates how effectively a multimodal, multi-model dashboard supports sensemaking for remote mental health assessment.

To assess the proposed IT artefact from a design perspective, the paper applies a set of design validity measures using a between-subjects online experiment with 150 participants. Participants were randomly assigned to one of three experimental conditions: (1) a full-feature condition in which the artefact included all design elements, (2) a condition in which the AI component was removed, and (3) a baseline condition in which key sensemaking-related design elements including the AI component and temporal cues were removed (corresponding to the removal of Design Elements 3–5 in the Paper 3 summary). For a detailed description of the experimental conditions, see the corresponding paper. Appendix A presents the experiment design activities in a chronological order.

First, the paper evaluates whether the artefact supports a deeper sensemaking of signals through analyzing the notetakings of participants during the experiment. Details of the coding process of notetaking are provided in the paper. Results show that participants using the proposed IT artefact engaged in more deeper sensemaking being attentive to different signals across modalities including the AI-generated predictions. In contrast, participants in the baseline condition predominantly focused on patterns within a single modality raw text suggesting a more fragmented sensemaking process when key tool design elements were absent. Furthermore, this was confirmed by tracking the participants interactions with the tools during the sensemaking process. Findings showed that participants using the proposed IT-artifact as a tool, made sense of data by connecting and comparing a broader set of signals, moving back and forth between signals of different modalities and the AI prediction of depression. By contrast, participants using the baseline tool lacking AI and fine-grained sensemaking design elements primarily engaged with single origin signals and largely ignored other components of the tool, which were limited to static summaries of emotions, facial muscle activity, and pitch.

Second, the evaluation assesses diagnostic performance where the findings showed that the proposed IT-artifact achieved the strongest performance, with higher sensitivity and specificity than the Baseline and No AI conditions. Figure 6 shows confusion matrices for depression assessment across the three experimental settings. The matrices indicate how often participants correctly and incorrectly classified patients as depressed or non-depressed, allowing us to compare how different forms of sensemaking support clinical assessments.

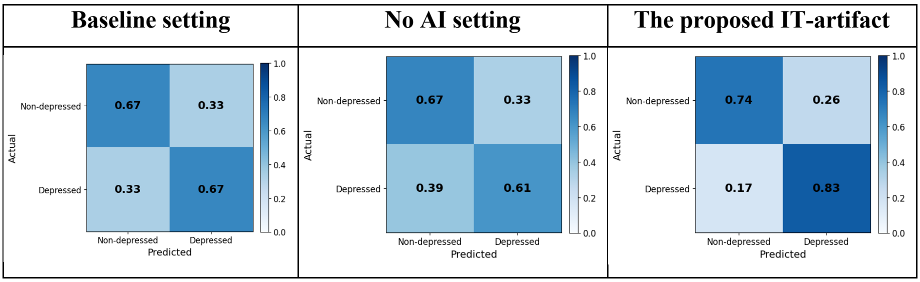

Figure 6 Accuracy of depressed and non-depressed cases accross experimental settings
Confusion matrices for depression assessment across three experimental conditions (from Paper 4).

These results provide outcome-level evidence that the dashboard's multimodal and design-guided features support more reliable assessments because of better supported sensemaking in remote assessment contexts, see Figure 7 below.

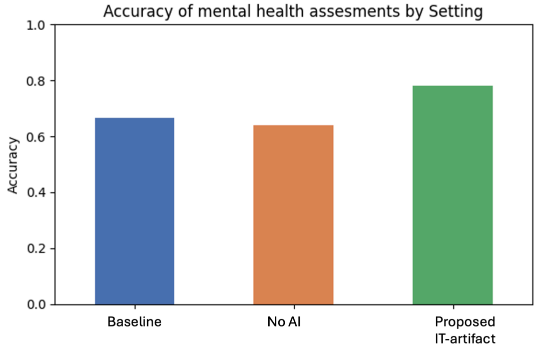

Figure 7 Accuracy across experimental settings
The bar chart shows mean task accuracy across the three system configurations: Baseline, no AI, and the proposed IT-artifact. Accuracy is computed as the proportion of correctly completed tasks (from Paper 4).

Third, the evaluation examines confidence in detecting the level of depression, moving beyond binary detection. Participants using the proposed IT-artifact as a tool felt more confident in assessing depression.

This paper allows the thesis to address both interpretive and contextual fit support by empirically evaluating how specific dashboard design elements shape healthcare practitioners' ability to make sense of complex, AI-generated data in mental health assessments. Overall, this paper answers the thesis research question on *"How to support sensemaking of data in healthcare"* by showing how a theory-guided, multimodal dashboard can support sensemaking of data for remote mental health assessment. The evaluation demonstrates that the proposed IT-artifact provides contextual fit for mental health assessments by deepening sensemaking (note-taking activity), enabling diverse sensemaking processes during interaction (cross-modal signal navigation), improving decision outcomes (accuracy) and strengthening sensemaking formation (confidence calibration).

More specifically, the paper advances *interpretive support* by empirically showing how sensemaking unfolds when clinicians use a data as a tool and how this process changes when AI component is included. Findings from cursor movements and click data analyses show that the proposed tool to support sensemaking guides attention and comparison across diverse set of cues: text, voice, facial expression, and AI model output. Importantly, the AI component appears to prompt reflection and verification where the findings show that users were in need to move in different levels of detail to make sense of data in healthcare rather than simply accepting them. As a result, this paper provides empirical evidence of how specific computational features supports interpretive support.

Finally, the paper supports *contextual fit* by demonstrating that the proposed IT artefact supports sensemaking in ways that align with the specific demands of remote mental health assessment. By embedding tasks that reflect psychiatric workflows, the evaluation tests whether the dashboard helps clinicians detect, integrate, and interpret behavioural and emotional cues in ways that match clinical practice. The results show that the proposed IT-artifact is not only technically effective, but also well suited to the context of mental health work, where decisions depend on combining multiple forms of evidence under uncertainty.

Paper 5

Ademaj, G, Sarker, S, Sarker, S., Abbasi, A. Collaborative sensemaking of data in precision public health: A phronesis process model

In this paper, let us shift the focus to data as practice view. This paper investigates how experts collaboratively make sense of data in precision public health, a domain where sensemaking of data is rarely straightforward and no single expert has all the contextual knowledge needed to understand what the data represent. From a data as practice perspective, the empirical setting shows that data meaning is discovered through situated practices, experience-driven judgement, and collaborative interaction among experts with diverse backgrounds.

As mentioned in the methods, Empirically, the paper draws on an interpretive research design based on 26 interviews with experts in Sweden's precision public health projects (see the paper appendix for the interview guide). Theoretically, it theorizes a process view on sensemaking with phronesis (practical wisdom) to explain how experts discern what data matters, bring contextual aspects into the collaborative space while remaining oriented to disease and population specific characteristics.

The paper provides *interpretive support* by developing a phronesis-informed process model that explains how collaborative sensemaking unfolds over time through distinct stages. The model makes visible how different forms of sensemaking emerge depending on the type of data being worked with and the stage of the collaborative process. Across stages, the analysis identifies two recurring experience-driven patterns in practice: sense-of-relevance prompts, which direct collective attention toward what may matter, and immersive episodes, in which experts collaboratively "sense the data" through interpretive practices of relating to shared reference points.

The paper also advances *contextual fit support* by showing that context is a set of stage-sensitive aspects of the data that need to be actively restored during collaborative sensemaking depending on how data show up. Drawing on the phronesis lens, allows us to dig into the nuanced/experience driven aspects through which experts relate their sense to disease-specific and population-specific meaning. More specifically, it does by providing tailored support by linking emerging interpretations to shared reference points, such as empirical facts in clinical practice, group considerations, decision goals, and acknowledged sources of uncertainty.

This paper answers the thesis research question on "*How to support sensemaking of data in healthcare"* by showing that sensemaking support must foreground both (1) the process through which sensemaking unfolds collaboratively over time with the different types of data and expertise, and (2) the contextual particulars that must be restored as data are interpreted in practice. This paper offers both a conceptual lens and an empirically grounded process model for understanding collaborative data sensemaking in complex, AI-infused healthcare environments. It adds theoretical depth to the thesis by explaining how meaning is constructed through joint reasoning and offers insights by surfacing phronesis mediators to show how healthcare context becomes embedded in data through collaborative data practices.

Discussion

Supporting sensemaking of data from multiple perspectives

Supporting the sensemaking of data in healthcare requires more than technical sophistication. The empirical evidence and findings of this thesis show that effective support depends on two complementary dimensions: interpretive support and contextual fit support. In this thesis, I have explored the dimensions where sensemaking support dimensions have different levels of interpretation and context has different levels of complexity. Through this, this thesis offers a cohesive framework that addresses this dual need by examining how meaning is constructed through human-AI collaboration (Paper 1), situated practices of data knowledge (Paper 2), theory informed design and evaluation of computational tools (Papers 3 and 4), and a phronesis process theorizing of collaborative sensemaking of data in precision public health (Paper 5).

By integrating conceptual, empirical, and design-based work, the thesis shows that sensemaking in healthcare is not a single cognitive process but rather a distributed process that unfolds across people, technologies, and institutional contexts. By framing data through three distinct roles as a practical tool, a socio-technical practice, and algorithmic intelligence, the thesis provides a multi-perspective answer to the research question: *How to support sensemaking of data in healthcare?*

This thesis addresses the multi-perspective nature of support required in healthcare environments, where data is increasingly complex, multimodal, and mediated through intelligent technologies. As healthcare data evolve from structured records to behavioral, multimodal, and algorithmically processed signals, the challenges of sensemaking also change fundamentally. What emerges from this research is that sensemaking must be understood and supported as a distributed and layered process. Using a multimethod approach (Sarker et al., 2025), each paper in the thesis contributes to this overarching goal by addressing different facets of the problem. Table 8 synthesizes how each paper contributes to both dimensions of sensemaking support across different data roles.

Tabel 8. Paper contributions

Thesis Research Question	**How to support sensemaking of data in healthcare?**		
Paper	**Interpretive Support**	**Contextual Fit Support**	**Data Role**
Paper 1 *Narrative Responsibility in Hybrid Intelligence*	Makes visible how interpretation unfolds in human-AI collaboration by specifying who interprets what, when, and with what responsibility as narratives are formed and revised in AI-supported work.	Provides a typology of interpretive responsibility in the different forms of human-AI collaboration *(synchronicity, reasoning, adjustment, continuity)*, explaining how narratives are co-constructed with AI-in-the-loop. This supports reflective, iterative interpretation.	Algorithmic Intelligence
Paper 2 *Data Knowledge and Knowing Data*	Theorizes four interpretive practices: *unveiling, balancing, acknowledging, realizing*, that explain how data becomes meaningful in practice. Supports non-technical practitioners in developing interpretive agency.	Emphasizes situated knowing by showing that what can be known from data depends on where it comes from and how it is embedded in routines, constraints, and tacit expertise.	Practice
Paper 3 *Dashboard Design for Mental Health Assessments*	Applies kernel theories (Integrative Sensemaking Theory and Signal Detection Theory) to inform the design of the dashboard features that help detect signals, compare cues, and evaluate data actively.	Grounds the artifact design in the specific diagnostic and cognitive demands of remote mental health assessment contexts (e.g., tracking signals over time, integrating multiple behavioral streams), ensuring tailored support for this particular disease and assessment context.	Tool and algorithmic intelligence

Thesis Research Question	**How to support sensemaking of data in healthcare?**		
Paper	**Interpretive Support**	**Contextual Fit Support**	**Data Role**
Paper 4 *Evaluation of the Dashboard*	Provides empirical, process-level evidence of interpretive support by showing how specific design elements change users' cue use during sensemaking with a tool (e.g., deeper integration in notes, interaction traces showing cross-modal navigation and back-and-forth checking between AI output and concrete cues).	Demonstrates that the artifact provides tailored support by testing it against clinical assessment tasks and clinical reasoning demands (detection, severity judgement, structured note taking summaries), showing the tool supports what is needed for this particular assessment context.	Tool and algorithmic intelligence
Paper 5 *Collaborative Sensemaking in Precision Health*	Explains how meaning is constructed collaboratively over time when no single expert can interpret the data alone, showing staged sensemaking and revealing the mechanisms that move teams from uncertainty to shared interpretations.	Shows that fit is achieved by actively restoring the context that data lacks: teams re-anchor interpretations in disease mechanisms, documentation practices, and population conditions, and what counts as "relevant context" shifts across stages and data forms.	Practice

Interpretive support varies significantly across the three data roles, each demanding different forms of making visible how data becomes meaningful. Within the data-as-practice role, Papers 2 and 5 reveal that interpretive support centers on uncovering how data becomes "known" through situated, socio-technical practices. Paper 2 theorizes data knowledge through practices like unveiling, balancing, and realizing, which reveal how non-technical actors engage in interpretive work to make data meaningful. Paper 5 extends this by making visible how collaborative sensemaking unfolds across experts practice and stages through phronetic processes. Concepts such as sense of relevance prompts and immersive episodes reveal how teams of diverse healthcare experts collectively notice what matters in the data at different stages, bring different forms of expertise into play across roles, and test emerging interpretations against contextual particulars. Here, interpretive support centers on showing how the collaborative sensemaking process unfolds by revealing how experts compare perspectives, surface uncertainties, and jointly construct meaning from incomplete and decontextualized data across different stages of their work. In the data-as-tool role, interpretive support is embedded in the design of computational artifacts. Papers 3 and 4 show how dashboard features structure how clinicians notice, compare, and evaluate multimodal and machine-generated cues. Access to raw signals, time-based visualizations, and ML outputs enables users to triangulate across text, voice, facial expression, and algorithmic predictions. The evaluation in Paper 4 shows that these design elements do not merely improve assessments but deepen the sensemaking process itself by making it more cautious to the different set of signals coming from the different modalities. Lastly, in the data-as-algorithmic intelligence role, interpretive support focuses on the evolving responsibility in narratives between humans and AI interaction. Paper 1 introduces a typology of narrative responsibility, illustrating how interpretive work unfolds through synchronicity, compulsive reasoning, and adaptive adjustments in hybrid intelligence systems. These findings show that interpretive support in healthcare must be tailored to the data's role, whether interpreted through collaborative sensemaking, encoded into visual interfaces, or co-constructed with intelligent systems. Paper 4 extends interpretive support for data-as-algorithmic-intelligence by showing how users engage with AI-generated signals during clinical sensemaking. Analysis of cursor movements and clicks reveals that when the overall AI prediction of depression is present, users do not simply accept it. Instead, they repeatedly move between the model output and multimodal behavioural cues, such as text, voice, and facial signals, while also navigating across those cues to build an integrated understanding of the case. This interaction pattern reveals how AI outputs actively shape how attention is distributed and how evidence is evaluated across different representations and stages of assessment. The findings show that rather than narrowing the sensemaking process, the AI signal becomes a focal point around which users compare, question, and revise their emerging frames. In this way, interpretive support makes visible the sensemaking processes with algorithmic intelligence by revealing how interaction is structured, enabling clinicians to relate model-based assessments to concrete clinical evidence while maintaining interpretive control over how algorithmic outputs enter their reasoning.

Contextual fit support ensures that tailored support is provided based on what is needed for specific disease contexts, and it takes on distinct forms depending on the data role. Within the data-as-practice role, contextual fit is achieved by providing tailored support through collaborative re-coupling of data to its disease-specific and population-specific origins. Paper 5 develops a phronesis-informed process theory showing how experts re-anchor fragmented, decontextualized data through practical reasoning and disease-specific anchoring. Grounded in interviews within different precision public health projects, the process model reveals different anchoring practices that allow teams of diverse healthcare practitioners to judge whether a data signal is plausible and meaningful for the specific population and disease condition under study. These mediators illustrate empirically how contextual fit is not inherent in data but must be actively re-assembled through situated interaction. Paper 2 likewise shows that what data "means" depends on the practices, roles, and constraints within which it is used. In the data-as-tool role, contextual fit support involves domain-specific design, ensuring tools are usable, interpretable, and grounded in the clinical and psychological realities of the intended setting. Papers 3 and 4 show that sensemaking tools must be tailored to the diagnostic and cognitive demands of mental health assessment. By grounding design requirements in psychology theory and evaluating them using clinical tasks such as diagnosis, summarization, and confidence rating, the thesis demonstrates whether the artefact fits the needs of that specific clinical context. In the data-as-algorithmic-intelligence role, contextual fit support concerns on providing tailored support for different forms of human-AI collaboration. Paper 1 explores this through variations in human-AI collaboration types, illustrating how different configurations influence the appropriateness and effectiveness of AI-generated narratives in healthcare contexts. Across all data roles, the findings show that contextual fit in healthcare takes different forms and needs different types of tailored support. When data is seen as part of clinical practice, it must be reconnected to the real experiences, judgments, and knowledge of healthcare professionals. When data is used through tools, those tools need to be carefully designed to match the specific clinical tasks and disease contexts they support. When data comes from AI systems, it must be presented in a way that healthcare professionals can understand, trust, and apply in their decision-making. This means that supporting contextual fit in healthcare requires different strategies depending on how the data is being used.

The findings show that supporting sensemaking requires accommodating multiple cognitive, interactional, and design needs. These range from making visible how to interact with systems and gain data knowledge across roles and stages (Papers 1, 2, 4), to revealing co-constructed reasoning among interdisciplinary teams and clinicians' intuitive grasp of patient behavior (Paper 5), to embedding theory-informed design and evaluation in computational artifacts tailored to specific disease contexts (Papers 3 and 4). This multi-perspective approach shows that supporting sensemaking of data in healthcare requires both making visible how sensemaking unfolds across roles, stages, and representations, and providing tailored support based on what specific disease contexts require. This is further evidenced through the typology of narrative responsibility (Paper 1) and the concept of data knowledge (Paper 2) which provide interpretive clarity on how data understanding unfolds within hybrid intelligence configurations. Furthermore, the phronesis-informed process model (Paper 5) surfaces the tacit, practical judgment needed to re-contextualize fragmented data across domains. Meanwhile, the design and empirical evaluation of a multi-modal dashboard (Papers 3) illustrate how interpretive and contextual fit can be built into tools that help healthcare practitioners distinguish between weak and strong signals, navigate modality conflicts, and interact with ML outputs in ways that enhance but do not replace clinical judgment. Finally, (Paper 4) provides empirical evaluation of the proposed IT-artifact to explore whether it supports what is needed for sensemaking of data in mental health assessments. The findings show that meaning of data depends on awareness, on the sources from where the healthcare data come from, on the situated actions of healthcare experts based on their tacit knowledge as well as to the way data is designed and interpreted through digital tools or to specific disease characteristics. Moreover, the thesis highlights the importance of alignments between the healthcare experts' skills and the design of algorithmic intelligence tools in healthcare, highlighting that synchronizing both expert and AI tasks is of importance for responsible sensemaking of data.

Ultimately, the thesis contributes a comprehensive framework for supporting sensemaking of data in healthcare: one that integrates making visible how sensemaking unfolds with providing tailored support for specific disease contexts, accounting for the shifting nature of data in the age of AI. By showing how sensemaking support must span from abstract theoretical grounding to fine-grained design decisions, the thesis provides a ground for future IS research and design in data-intensive and sensitive domains. The thesis argues that supporting sensemaking in healthcare requires moving beyond earlier concerns with physical signals and organizational events (Weick 1995; Maitlis 2013) toward grappling with how experts interact with diverse, ML-processed data and algorithmic tools (Abbasi et al. 2024). These interactions give rise to new forms of complexity that earlier work did not anticipate (Kay 2022). The findings and empirical material showed that healthcare practitioners now encounter data in multiple, simultaneous forms data that functions as a tool for decision-making, as something woven into clinical practice and digital systems that needs to be made sense of and shared with others, and as AI-generated output. Each form presents distinct sensemaking challenges from tool design to concerns about sensemaking with algorithmic outputs and collaborations between experts in the clinical floor and the ones who have technical knowledge on analyzing this type of data. The thesis develops a multi-perspective framework that addresses how meaning, responsibility, and clinical relevance emerge differently depending on whether data is encountered as tool, practice, or AI.

Theoretical Implications

This dissertation advances IS theory by offering a multi-perspective, socio-technical understanding of how to support the sensemaking of data in healthcare. While IS research has for a long time studied the relationship between information, technology, and decision-making, it has paid less attention to the nuanced, context-sensitive interpretive processes through which data becomes meaningful in practice (Aaltonen et al., 2023). This work extends IS research by explicitly theorizing how data becomes meaningful through interaction, collaboration, and tool design within clinical settings marked by uncertainty, interpretive dependence, and algorithmic mediation. This thesis contributes theoretically informed and practically oriented support for sensemaking of data in healthcare.

The primary theoretical contribution lies in the development of a framework that delineates two essential dimensions of sensemaking support: interpretive support and contextual fit support. This dual framing responds directly to long-standing concerns in IS about the under-theorization of how meaning is constructed through data use (Orlikowski & Iacono, 2001; Lycett, 2013; Sarker et al., 2019). As Baird et al. (2025) emphasize, healthcare problems are multifaceted, context-sensitive, and not amenable to one-size-fits-all solutions. The challenge of making sense of healthcare data is further compounded by the increasing diversity in how data is used, ranging from algorithmic intelligence to collaborative practice and tool-mediated use. These challenges necessitate a multi-perspective conceptualization of sensemaking support, one that acknowledges the varying interpretive and contextual demands across different data roles.

The concept of interpretive support shows how sensemaking of ambiguous or complex data unfold by making visible the supporting mechanisms and processes through which practitioners come to understand data. It therefore concerns the exploratory work required to make data meaningful and usable, particularly in environments characterized by complex expert interaction, complex forms of ML-derived data that require arrangement, and evolving relationships between experts and ML systems. While prior IS literature has focused on sensemaking (e.g., Vlaar et al., 2008; Abbasi et al., 2018), it has not systematically unpacked what kinds of support are needed across different roles of data. This thesis contributes by a typology of interpretive mediation in human-AI collaboration (Paper 1), a conceptualization of data knowledge that synthesizes literacy, practice, and contextualization (Paper 2), a computational interpretation to support sensemaking of data (Paper 3, 4) and process model of phronesis-based collaborative sensemaking (Paper 5). Hence, interpretive support captures the exploratory and interactional processes through which data becomes intelligible, such as through phronetic mediators (Paper 5), responsible narrative practices (Paper 1), or computational interpretive support of the data (Papers 3 and 4).

Contextual fit, by contrast, addresses how this meaning aligns with the situated demands of clinical practice, attending to disease-specific reasoning, professional roles, and domain constraints (Papers 2, 3, 5). This thesis advances the concept of contextual fit by responding to foundational calls in IS research to theorize technological artifacts in relation to their specific domains of use. Orlikowski and Iacono (2001) originally argued that the role of technology cannot be understood in isolation from the context in which it is used, and Hong et al. (2014) further emphasized that the characteristics of technological artifacts must be situated at the core of context-specific theorizing. Building on this tradition, the thesis demonstrates that supporting sensemaking of data in healthcare demands understanding, design and evaluation approaches that actively embed clinical, disease-specific, and role-based requirements into the artifact itself. Paper 1 adds to the idea of contextual fit by providing tailored support for narrative responsibility across different forms of human-AI collaboration and the situational demands each creates. The study demonstrates that effective sensemaking requires not only humans adapting to the task and the AI output, but also AI systems modulating their interpretive engagement based on human expertise and context. This highlights the co-adaptive nature of contextual fit**,** where both actors must remain sensitive to organizational, task, and epistemic conditions for sensemaking to be responsible and meaningful. Papers 3 and 4 exemplify this by grounding the design of a mental health dashboard in psychological theory, signal detection needs, and integrative sensemaking practices. Paper 5 extends this by focusing on the nuances and showing how context is reassembled and re-coupled through phronesis collaboration among experts interpreting fragmented data. Paper 5 extends this by showing how context is reassembled and re-coupled through phronetic collaboration among experts interpreting fragmented data.

The integrated framework offers flexibility to support multiple data roles, as practice, tool, and algorithmic intelligence (Xu et al., 2024). By mapping interpretive and contextual fit support across these roles, the dissertation contributes theoretically, refining existing IS discussions of the IT artifact (Orlikowski & Iacono, 2001) and the axis of cohesion (Sarker et al., 2019), offering a coherent framework for theorizing how the design, use, and meaning of data unfold in practice. This contribution is significant because it moves beyond treating data as a monolithic concept, instead revealing how different data roles create distinct sensemaking demands that require different forms of support. The data-as-practice view reveals sensemaking as a collaborative, phronetic process embedded in professional routines and tacit knowledge. The data-as-tool view positions sensemaking support within the design of computational artifacts that mediate interpretation through visual and interactive features. The data-as-algorithmic-intelligence view foregrounds the distribution of interpretive responsibility between human and AI actors, where sensemaking becomes a co-constructed narrative process. By theorizing sensemaking support across these three data roles, the thesis provides IS scholars with a nuanced vocabulary for addressing the heterogeneity of data use in contemporary organizations.

The framework enables tailored sensemaking support that aligns with user roles, settings, and interpretive challenges. Together, these concepts push IS literature to move beyond cognitive or technical aspects of sensemaking of data (Mesgari and Okoli 2019), offering a socio-technical, situated account of how data is jointly interpreted and embedded in context-sensitive environments. The thesis argues that the work needed for collaborative sensemaking of data cannot be abstracted from its temporal, spatial, or disciplinary contexts. This moves beyond generic solutions to purpose-specific, use-sensitive support for responsible and meaningful data use. The framework demonstrates that to support sensemaking of data in healthcare is not only to interpret data, but to shape the conditions through which meaning, responsibility, and clinical relevance emerge in specific disease contexts.

Second, the dissertation contributes a multi-method approach (Sarker et al., 2025) for analyzing sensemaking from different dimensions and perspectives. Using conceptual, empirical, and design-based methods, the thesis develops conceptual, processual, and design contributions tailored to each form of sensemaking support that aligns with the nature of the data. This dissertation adopts a multimethod research approach, leveraging two distant but complementary methodologies, literature review and interpretive studies, and design science research to comprehensively understand and support sensemaking of data in healthcare. Rather than seeking tight methodological fusion, the thesis deliberately employs an interlayered integration strategy (Sarker et al., 2025) where distinct methods operate in parallel layers, each addressing specific challenges associated with different data views (practice, tool, algorithmic intelligence), and each contributing either theoretical insight, practical design guidance, or both. This form of integration is particularly well-suited given the high methodological distance between the qualitative literature review and interpretive studies (Papers 1, 2, 5) and the design science studies (Papers 3, 4). This multimethod contribution advances IS body of knowledge by demonstrating how methodological diversity can be applied to offer more nuanced theoretical and practical understanding of complex sociotechnical phenomena. By adopting an interlayered integration strategy that respects methodological distance while achieving conceptual coherence through the dual-dimensional framework, the dissertation provides a methodological exemplar for IS research addressing multifaceted, context-sensitive problems where exploratory understanding and nuanced support must coexist (Baird et al., 2025).

Third, this dissertation extends IS contributions to computational design science (Abbasi et al. 2024), a key area for health-related research in the field (Baird et al., 2025*)*. Papers 3 and 4 exemplify this by designing and evaluating a multi-modal, multi-model dashboard that operationalizes interpretive and contextual fit through computational visualization, enabling mental health practitioners to meaningfully interact with complex algorithmic data outputs. In doing so, the thesis addresses the challenge that “existing dashboards fall short for addressing complex societal challenges such as mental health” (Baird et al., 2025, p.576), offering theory-informed design principles that go beyond data integration toward interpretive usability and context sensitivity. This thesis advances design oriented IS research by addressing a critical shortcoming in existing computational dashboard designs: their limited capacity to support interpretive depth and contextual fit in complex domains such as mental health. Responding to these needs and drawing from Signal Detection Theory and Integrative Sensemaking Theory, the proposed design and evaluation of a multi-modal mental health dashboard illustrate how IS scholars can embed sensemaking support into artifacts that are contextually grounded and theory-informed (Ademaj, Zhang, et al. 2025). This contributes to IS design science by showing how theory can inform not only the design of functionality, but the computational interpretive and contextual support embedded in those functionalities. Furthermore, the dashboard designed in Papers 3 and 4 does not simply visualize algorithmic data outputs but rather it foregrounds the conditions under which those outputs are interpretable and clinically meaningful. This addresses longstanding IS concerns about the risk of decontextualized algorithmic decision support (Lebovitz et al., 2021) by demonstrating how algorithmic data outputs can be translated into actionable insight when embedded in tailored, interpretively supportive design elements.

In summary, this dissertation makes three interrelated contributions to IS research by offering theoretically informed and practically oriented support for sensemaking of data in healthcare. First, it develops an integrated framework of interpretive support and contextual fit support that offers flexibility to support multiple data roles, enables tailored sensemaking support aligned with user roles and settings, and moves beyond generic solutions to purpose-specific, use-sensitive support for responsible and meaningful data use. Second, it contributes a multi-method approach that develops conceptual, processual, and design contributions tailored to each form of sensemaking support: process models for collaborative interpretation (practice view), computational designs for data tools (tool view), and interpretive frameworks for responsible interaction with algorithmic outputs (algorithmic view). Third, it advances the design of computational artefacts by demonstrating how tools can be designed to support sensemaking of complex data in the context of mental health assessments.

Practical Implications

This dissertation provides actionable insights for practitioners, system designers, and healthcare institutions aiming to improve how data is meaningfully interpreted and used in complex clinical environments.

First, the thesis emphasizes that making sense of data in healthcare is not a purely technical task, but a collaborative, interpretive effort. This insight has practical implications for how teams are organized and how data processes are supported. For example, in precision public health (Paper 5), experts from different domains often hold only partial knowledge about data. The study shows that interpretive support through attention prompts, grounding narratives, and alignment work should be intentionally facilitated.

Second, the thesis contributes concrete design guidelines for computational tools that support interpretive flexibility. The design and evaluation of a multi-modal mental health dashboard (Papers 3 and 4) offer five actionable features that practitioners and system developers can implement: (1) providing access to raw cues (text, audio, visuals), (2) supporting identification of systematic behavioral patterns, (3) enabling recognition of cross-modal signals, (4) exposing ML model confidence and logic, and (5) supporting multi-level exploration of patient data. These features not only improve usability but directly support more reflective, accurate, and context-sensitive clinical interpretations. Furthermore, it illustrates how to embed contextual sensitivity directly into the way algorithmically derived data is presented and interpreted. This ensures that healthcare systems support clinical reasoning, rather than override it, and helps bridge the gap between computational processing and real-world healthcare decision-making.

Third, the findings offer guidance for responsible human-AI collaboration in clinical settings. Paper 1 introduces the concept of narrative responsibility, demonstrating how clinicians can take ownership of AI outputs through iterative reflection, alignment with clinical reasoning, and ongoing adaptation. The typology shows awareness to healthcare practitioners on how responsibility can be applied in the different forms of interacting with AI. Further, the typology offers guidance on healthcare practitioners working with different types of AI to better understand and adjust to the context in which the AI is used. It supports ongoing alignment between what goes into the system and what comes out, making it easier to spot and correct insights that don't fit the situation, and turn them into ones that do.

Fourth, the thesis encourages healthcare leaders and IT departments to reframe data projects not just as implementation efforts, but as interpretive and context-coupling initiatives. Paper 2 shows that meaningful data use requires practitioners to "know" data. This involves unveiling its origins, aligning it with local expertise, and embedding it into situated routines. For healthcare organizations, this means that data literacy efforts must go beyond technical training, and include discussions about data meaning, clinical context, and interpretive variation.

Lastly, the theoretical framework developed in this thesis offers a tool for system designers and healthcare leaders to assess which form of support: interpretive, contextual, or both is needed in different settings depending on whether data is used as a tool, used through practice, or mediated by AI. This can guide tailored intervention strategies from interface design to workflow structuring and inter-professional training to better support sensemaking of data.

In summary, this dissertation delivers a set of practically grounded, context-aware, and theory-informed insights for improving how healthcare data systems are designed, implemented, and used. It supports professionals and designers in creating data environments that not only function well technically, but also promote reflective, collaborative, and clinically relevant interpretations of complex and often ambiguous data.

Limitations and future research directions

This dissertation offers a multi-perspective framework for supporting the sensemaking of data in healthcare, grounded in conceptual, empirical, and design-oriented support. While the findings contribute to IS research and practice, it is important to reflect on the limitations of this work and the opportunities it opens for future scholarship.

First, the scope of this research is focused within clinical decision-making contexts in healthcare, such as diagnosis, monitoring, or patient assessment. As a result, the findings may have limited generalizability to other non-clinical healthcare data use scenarios, such as health policy planning, public health strategy formulation, or administrative decision-making. These contexts often involve different types of data, longer time horizons, and different actors (e.g., policy analysts vs. clinicians), which may call for different forms of sensemaking support. Based on this, future research could examine how the dual dimensions of interpretive support and contextual fit manifest in these non-clinical settings, testing the framework's transferability and revealing whether additional dimensions of sensemaking support are needed.

Second, the thesis is contextually bound to the healthcare sector. Although the theoretical framework particularly the dual dimensions of interpretive support and contextual fit may be applicable to other high-stakes, data-intensive domains (e.g., education, law, crisis response), these assumptions remain untested outside healthcare. Future work can focus on understanding the sensemaking needs for other contexts.

Third, while the thesis offers insights grounded in practice, it would be interesting to understand deeper nuanced through observations in the healthcare settings. This means that certain aspects of sensemaking such as micro-level interactions between clinicians and AI tools, embodied and tacit dimensions of collaborative interpretation, or situated healthcare actions under time pressure remain underexplored. Future work can focus on observing collaborative practices during sensemaking of data as well as conduct observational studies to understand the interactions of healthcare practitioners with the healthcare AI tools and using them to share insights with the other experts. Further, future research can focus on conducting longitudinal studies to explore how sensemaking support needs evolve over extended periods of system use and institutional adoption.

Fourth, Papers 3 and 4 focus on a single artifact: a multi-modal mental health dashboard within a specific disease context. While this allowed for deep, theory-informed design and rigorous evaluation, the findings about computational interpretive and contextual fit support are tied to particular design choices. Future design science research could explore alternative computational approaches such as conversational interfaces, immersive visualizations, or collaborative annotation tools to understand which design patterns are most effective under which conditions. Comparative studies across multiple artifacts and contexts would help build a more generalizable design theory for sensemaking support.

Finally, while the thesis offers practical contributions through design requirements and process models, it does not address the organizational, regulatory, or ethical infrastructures needed to implement and sustain sensemaking support in real-world healthcare settings. Future research could examine how healthcare organizations can build capacity for interpretive and contextual fit support and how such efforts interact with existing regulatory frameworks for AI in healthcare.

In reflecting on these limitations, I recognize that they are opportunities for deeper engagement with the complexities of sensemaking in healthcare and beyond. Each limitation points toward a productive line of research that could extend, refine, or challenge the framework developed here. By acknowledging these boundaries, I hope to invite future scholars to build on this work in ways that are attentive to different practical aspects as the role of data may continue to evolve.

Conclusion

This dissertation has explored how to support the sensemaking of data in healthcare. As data becomes increasingly digitized, multimodal, and shaped by intelligent systems, the fundamental challenge facing healthcare practitioners has shifted from gaining access to data to making sense of it.

To address this, the thesis develops a multi-perspective framework for supporting sensemaking, grounded in five interrelated papers and a multi-method research design. The framework begins from the premise that data in healthcare is used in different ways as a practice, a computational tool, and as algorithmic intelligence. The thesis shows that each role introduces distinct challenges for sensemaking. Through examining these roles, the thesis identifies and theorizes two foundational dimensions of support: interpretive support, foregrounding how sensemaking happens across roles, stages, and representations in healthcare practice, and contextual fit support, which provides tailored support based on what is needed for specific disease contexts, ensuring that data remains anchored in the clinical, organizational, and disease conditions where decisions unfold.

The thesis demonstrates the value of a multimethod approach for addressing this complexity. By integrating literature review and interpretive studies with design science research, it shows how different methodological lenses can reveal different facets of the sensemaking challenge. Literature review and interpretive studies provide theoretical and empirical depth into how data becomes meaningful through situated practices and collaborative reasoning. Design science research provides theory-informed practical interventions that operationalize interpretive and contextual fit support through computational design. This methodological pluralism enables both theoretical depth and practical-oriented support for sensemaking of data in healthcare.

The thesis makes three central contributions to IS research. First, it develops an integrated framework of interpretive support and contextual fit support that offers flexibility to support multiple data roles, enables tailored sensemaking support aligned with user roles and settings, and moves beyond generic solutions to purpose-specific, use-sensitive support for responsible and meaningful data use. This framework advances IS research on data use in complex, sensitive domains by responding to long-standing calls for more nuanced theorization of how meaning is constructed through data use. Second, the thesis contributes a multimethod approach that develops conceptual, processual, and design contributions tailored to each form of sensemaking support: process models for collaborative interpretation (practice view), computational designs for data tools (tool view), and interpretive frameworks for responsible interaction with algorithmic outputs (algorithmic view). This demonstrates how methodological diversity can be strategically harnessed to produce richer theoretical and practical understanding of complex sociotechnical phenomena. Third, it advances the design of computational artefacts by demonstrating how tools can be designed to support sensemaking of complex data in the context of mental health assessments.

These contributions demonstrate that sensemaking processes vary a lot across different roles of data and that support must be differentiated accordingly. The thesis reveals how interpretive understanding and contextual complexity play out across multiple levels: individual, collaborative, and algorithmic and shows that effective support requires attending to each of these levels in ways that are sensitive to the specific nature of the data role. For the practice view, sensemaking unfolds through phronetic collaboration among experts who must re-anchor fragmented data in disease mechanisms, population conditions, and clinical knowledge. For the tool view, sensemaking is mediated through computational artifacts whose design features structure how practitioners notice, compare, and evaluate multimodal and machine-generated cues. For the algorithmic intelligence view, sensemaking becomes a co-constructed process where interpretive responsibility is distributed between human and AI actors, requiring explicit frameworks for narrative alignment and adaptive adjustment.

In conclusion, this thesis contributes a comprehensive and nuanced understanding of how to support the sensemaking of data in healthcare. The thesis shows that supporting sensemaking is a layered and distributed process requiring alignment between system design, professional practice, and interpretive agency. It reveals that meaning does not reside in data itself, but must be actively discovered, constructed, and re-coupled to context whether through expert phronesis, tailored computational interpretations for disease characteristics, or alignment between health experts and the intelligent technologies they use. By bringing together practice-based, computational, and algorithmic perspectives, the dissertation provides a foundation for more responsible and context-sensitive data use in healthcare. It also opens up avenues for future research to further develop and test ways of supporting sensemaking as healthcare data, technologies, and forms of expertise continue to evolve.

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Appendix A

Table Appendix A Experiment activities

Activity No	Activity type	Activity description
1	Apply for ethical advisory opinion in Sweden	We were given approval that for this experiment there is no need to apply for ethical application in Sweden.
2	Apply for IRB approval in USA	This study has been reviewed and approved by the University of Notre Dame Institutional Review Board, IRB protocol ID 25-03-9149.
3	Recruitment for a Pilot study	30 participants have been recruited using Prolific with a background in healthcare such as nurses, student of psychology, social workers, medical student and so on. The survey experiment has been designed in Qualtrics.
4	Recruitment for the Full experiment study	150 participants have been recruited using Prolific with a background in healthcare such as nurses, student of psychology, social workers, medical student, biology background, biomedicine and so on. The survey experiment has been improved from the pilot study and further designed in Qualtrics.
5	Consent (applies to both Pilot and Full experiment)	Participants have provided consent prior to participation in the survey, including the option to withdraw from the study at any time without penalty. Consent have been obtained electronically. Participants who did not give consent were not allowed to continue the survey and thus were returned to Prolific.
6	Random Assignment to Experimental Setting (applies to both Pilot and Full experiment)	After providing consent, each participant will be randomly assigned to one of the three experimental settings that reflect different design variations of the dashboard, see Paper 3 and 4 for more details: i) Full dashboard with all features (multimodal signals + ML confidence indicators); ii) Baseline condition (audio and transcript, summary of facial muscles, emotions and pitch) iii) Dashboard without ML confidence scores and ML depression indication prediction.

Activity No	Activity type	Activity description
7	Session Structure (applies to both Pilot and Full experiment)	Each session has lasted approximately 1 hour and consist of the following parts: Introduction and Tutorial (~5 minutes): Participants received a brief overview of the study and a tutorial tailored to their assigned dashboard condition, explaining the features and how to interpret the visualizations. Quiz : Participants were given a quiz with four questions to ensure that they have followed the tutorial and understood the tasks correctly. Dashboard Evaluation Tasks (~25–30 minutes): Each participant have been shown three patient data in the assigned dashboard. This resulted into 450 data points from where we have based our evaluation of the proposed IT-artifact. For each shown data in the dashboard, they completed three tasks: (i) First task: a binary classification task to determine whether the individual appears to show signs of depression or not. ii) a confidence in assesment rating task (Likert scale 1-7) (iii) a written note-taking summary describing the person's behavioral and emotional patterns. The note-taking tasks were specifically asking for notes on Appearance, Speech, Emotion and Though Content. Post-Task Survey (~5–10 minutes): Participants completed a brief survey evaluating the perceived usefulness, ease of use, and future of the dashboard focusing on the different dashboard elements. Further participants completed a ranking task of the dashboard components based on usefulness and ease of use.
8	Data Collection (Applies to both Pilot and Full experiment)	- Depression classification decisions (binary) from task (i). - Rating of confidence level from task (ii). - Written justifications and summaries from task (iii). A short post-task survey measuring perceived usefulness, ease of use and raking the different IT-artifact visualizations components. - Tracking click number and mouse movements in the dashboard during participants sensemaking with the tool.

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