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Give me 3W1H: A Bibliometric View on Accountable AI

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Completed Research Paper

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Abstract

Accountability is crucial to make stakeholders of Artificial Intelligence (AI)-based systems justify their actions, thereby explaining the harm such systems cause to AI users. Due to the importance of accountability in the context of AI, accountability was introduced into IS research through literature reviews. Therefore, while IS research's understanding of accountability covers the necessary depth, it comes at the expense of its essential breadth. Using a bibliometric analysis with 19,978 English-language papers, we shed light on the essential breadth posing three W- and one H-questions (When, What, Whereof, and How). Therefore, we contribute to IS research by highlighting the urgent need to revise existing definitions of accountability in the context of AI and establish them in IS research. We argue that a missing revision leads to non-transferrable findings within IS research. Accordingly, this study serves as a starting point for adapting definitions and creating a shared understanding in IS research.

Keywords: Accountability, Artificial Intelligence, Bibliometric Analysis, Information Systems, Literature

Introduction

Artificial Intelligence (AI)-based systems increasingly affect our society in more and more domains and contexts, such as sales, finance, and medicine (e.g., Adam et al., 2022; Jung et al., 2018; Jussupow et al., 2022). For instance, healthcare professionals use AI-based systems to diagnose their patients (e.g., Jussupow et al., 2022). Within such uses of AI-based systems, ethical issues for AI users can arise from AI-based systems and their design (e.g., Berente et al., 2021; Spiekermann et al., 2022). If such ethical issues arise, accountability ensures that AI stakeholders (e.g., AI developers, managers, and users) explain and justify their actions causing the issues (e.g., Martin, 2019; Shin & Park, 2019; Wieringa, 2020).

In this context, *accountability* describes AI stakeholders' need to justify their behavior to others (Tetlock, 1985; Wieringa, 2020) and has two advantages: First, it encourages AI stakeholders to explain their AI-based systems (e.g., Novelli et al., 2023), and second, it makes it more likely that AI stakeholders follow ethical guidelines (e.g., Bovens, 2007; Martin, 2019). Following ethical guidelines is essential to ensure that designed and implemented systems do not cause harm to AI users affected by the AI-based system in later operations. Examples of AI-based systems that caused harm to AI users are algorithms used in U.S. hospitals that discriminated against black patients through racially biased data (Obermeyer et al., 2019) and Amazon's recruiting tool that discriminated against women (Dastin, 2022). Given these examples, accountability should be a priority in IS research in developing AI-based systems to prevent harm from such systems. However, accountability in IS research is not only crucial to avoid ethical issues for AI users but also serves to explain a variety of effects. Moreover, accountability can encourage AI users to follow the recommendations of AI-based systems (Adam, 2022). In particular, AI developers' perceived (intrapersonal) accountability can lead to less job satisfaction (Schmidt et al., 2023). These examples illustrate that accountability in the context of AI is becoming increasingly important in IS research, so a shared understanding of accountability is highly important.

While the term AI underwent many scientific definitions (e.g., Collins et al., 2021; Min, 2010; Talbi, 2021), the meaning of accountability remained unclear and fuzzy. One possible reason may be that the basic understanding (i.e., the need to justify one's behavior to others) is understood differently in research: For example, in public administration, accountability is equated with four concepts, namely, responsibility, control, responsiveness, and dialogue, giving accountability an expansive definition and understanding (Mulgan, 2000). In contrast, in healthcare, accountability is used, among other things, to ensure job autonomy (Batey & Lewis, 1982). Since IS research is focused on interdisciplinary research, such as computer science (e.g., Asatiani et al., 2020) and psychology (e.g., Schmidt et al., 2023), the broad definitions and understandings of accountability affect IS research's understanding of accountability. In existing IS literature reviews, a definition and understanding of accountability have been introduced into IS research (e.g., Novelli et al., 2023; Wieringa, 2020). Due to the methodologies chosen, literature reviews cover the depth of the literature but overlook the breadth of accountability. For example, one definition of accountability in IS research is a relation between an actor and a forum, where actors must justify themselves to forums (e.g., Horneber & Laumer, 2023; Novelli et al., 2023; Wieringa, 2020). Through this understanding, it is unclear what precisely is meant by accountability, which is why the current definition and understanding are fuzzy when applying them. This leads to an arbitrary softening of the term when adapting and inspiring interdisciplinary research in IS research. Accordingly, getting an oversight of what accountability can refer to in order to evaluate existing definitions and understandings is crucial. Therefore, a breadth view must be considered for accountability to understand this concept in the context of AI.

To gain the needed breadth view, this study focuses on accountability in the context of AI, using existing knowledge from interdisciplinary research to draw conclusions from interdisciplinary to IS research. For this, we are guided by previous research conducting bibliometric analyses (e.g., Kahdan et al., 2022; Wamba et al., 2021; Zhang et al., 2021). Bibliometric analyses help clarify unclear and fuzzy terms or concepts by automatically looking at and evaluating large amounts of literature (e.g., Kahdan et al., 2022). For this purpose, the terms or concepts are approached using various analyses to obtain an overview (e.g., Kahdan et al., 2022; Zhang et al., 2021). Their results lead to the interpretation of the terms and concepts in the literature and the question of how existing definitions are sufficient (e.g., Wamba et al., 2021; Zhang et al., 2021). Accordingly, we address three W- and one H-question: (1) Since **when** does research consider accountable AI, (2) **what** does accountable AI mean in research, (3) **whereof** is accountable AI affected, and (4) **how** does IS research use accountable AI compared to interdisciplinary research. By answering these three W- and one H-question, we intend to understand accountability in the context of AI better and make the fuzzy and unclear term more tangible in IS research.

We conducted a bibliometric analysis to answer our raised questions, as previous research has shown that this methodology suits well to answer such questions (e.g., Kahdan et al., 2022; Wamba et al., 2021; Zhang et al., 2021). In doing so, we approximate the understanding of accountability in the context of AI by using state-of-the-art techniques such as Word2Vec word embeddings (Mikolov et al., 2013) and co-occurrences maps (Kahdan et al., 2022; van Eck & Waltman, 2018) in addition to descriptive analyses (Krzywinski et al., 2009; Wamba et al., 2021; Zhang et al., 2021). For these analyses, we use titles and abstracts extracted from Web of Science (`https://www.webofscience.com/`). Our corpus includes 19,978 English-language papers addressing accountability in the context of AI, of which 3,099 publications are from the IS research area.

With our bibliometric analysis, we objectively view the understanding of accountability in the context of AI. In doing so, we gain transparency and arguments for the need for IS research to adjust existing definitions and understandings of accountability in the context of AI. As a result, we significantly contribute to IS research by highlighting future potential problems caused by a continued lack of a shared understanding of accountability. Especially the continued lack indicates that IS research findings are often not transferable to other studies within IS research and, therefore, a common ground for communication. While we can explicitly highlight the need with our bibliometric analysis, our study is limited to providing transparency and arguments for adjusting definitions and understandings in IS research. Therefore, this study should serve as a starting point for future IS research about which aspects must be strengthened and highlighted in subsequent definitions and understandings.

Theoretical Background

Conceptual Understanding of Accountability

Accountability is an unclear and fuzzy term that finds application in various scientific areas such as healthcare and public communication (e.g., Batey & Lewis, 1982; Choi & Valente, 2022; Solomon et al., 2022). It describes the need to justify one's behavior to others (Tetlock, 1985; Wieringa, 2020). In this context, accountability can be characterized by six facets (Day & Klein, 1987), namely (1) *trigger* (i.e., an event that triggers the accountability process), (2) *entity* (i.e., person or organization that is held accountable for what happened), (3) *situation* (i.e., action or situation, for which the entity is accountable), (4) *forum* (i.e., an individual, organization, or institution before which an entity is accountable), (5) *criteria* (i.e., criteria for judging an action or situation), and (6) *sanctions* (i.e., consequences for the entity as a result of the accountability processes). Another understanding of accountability describes it as a relationship between an actor (*entity*) and a *forum*, whereby actors must justify their actions to forums and receive *sanctions* or *rewards* (Bovens, 2007). Thus, existing understandings are picked up (e.g., Day & Klein, 1987) and put in relation to each other. This relation is important because accountability serves various functions in interdisciplinary research: For example, in healthcare, accountability is used, among other things, to ensure job autonomy (Batey & Lewis, 1982), while in public administration, accountability aims to promote public dialogue (Mulgan, 2000). Finally, in IS research, accountability increases job satisfaction (Schmidt et al., 2023), increases the intention to follow the advice of an AI-based system (Adam, 2022), and provides frameworks to manage accountability in practice (Raji et al., 2020).

Accountable AI in Literature

This paper follows previous IS research on AI and defines AI-based systems along the three facets: autonomy, learning, and inscrutability (Berente et al., 2021). Autonomy describes how AI-based systems can act without human involvement in a given interaction space. Therefore, humans cannot or only partially intervene in the autonomous decisions of AI-based systems (Berente et al., 2021; Citron & Pasquale, 2014). Learning describes how AI-based systems can use new data to improve themselves over time (Berente et al., 2021). Accordingly, AI-based systems will evolve iteratively (Berger et al., 2021). Inscrutability describes the opacity of an AI-based system, making its operation incomprehensible to humans. Humans may understand the theoretical concepts behind AI algorithms but cannot understand why a specific output was generated (Berente et al., 2021). Such AI-based systems can be implemented by using AI techniques like *machine learning* algorithms, which can be categorized into *supervised*-, *unsupervised*-, and *reinforcement-learning*. Examples of *machine learning* algorithms are *deep learning*-, and *neural networks*-algorithms (e.g., Collins et al., 2021; Kahdan et al., 2022; Talbi, 2021). Using these AI algorithms may create new ethical problems that AI stakeholders have to justify to others. Accountability thus holds a crucial function to ensure that ethical problems are prevented or resolved at any time. Considering accountability in the design of AI-based systems is thus of great importance (e.g., Martin, 2019; Shin & Park, 2019). In doing so, IS research describes accountable AI as "how institutions, organizations, and individuals can govern ML [machine learning] systems and how developers and providers of ML systems can fulfill their accountability obligations" (Horneber & Laumer, 2023, p. 7) or "accountability as a relation of answerability requiring authority recognition, interrogation and limitation of power" (Novelli et al., 2023, p. 11). Therefore, definitions already exist but are quite broad and unclear. Consequently, what accountability in the context of AI refers to remains open and unclear (e.g., Horneber & Laumer, 2023; Novelli et al., 2023), so it is important to investigate accountability in more depth to better understand accountable AI. To investigate accountable AI in more depth, we first investigate accountability from a literature perspective and derive eight different terms and synonyms used for accountability, which we describe in the following (i.e., *responsiveness*, *responsibility*, *explainability*, *explicability*, *transparency*, *auditability*, *liability*, and *integrity*).

The terms with the closest meaning to accountability are *responsiveness* and *responsibility* (Bovens, 2007; Hall et al., 2017; High-Level Expert Group on Artificial Intelligence, 2019; Jobin et al., 2019; Mulgan, 2000). *Responsiveness* aims to ensure that an actor responds to a decision on time. Thus, *responsiveness* reinforces the need to justify one's behavior to others and introduces a temporal dimension to accountability. In addition, *responsiveness* focuses on the existence of a forum (Mulgan, 2000). Conversely, *responsibility* involves avoiding harm to users using IS (Kaur et al., 2022). At the same time, *responsibility* requires identifying someone responsible for one's actions (e.g., Bovens, 2007; Mulgan, 2000). This aspect is essential in developing and operating AI-based systems because these processes involve many stakeholders. The question thus arises as to who is responsible for which processes of AI-based systems, and as a result, must justify themselves to others by being held accountable (e.g., Cooper et al., 2022; Jobin et al., 2019). In this regard, some of the literature distinguishes to whom (i.e., entity versus forum) *responsibility* must apply: "Although responsibility and accountability have been used interchangeably in some of the literature, Frink and Klimoski (1998) and others have distinguished *responsibility* from accountability by suggesting that accountability imposes the additional requirement of an external audience." (Hall et al., 2017, p. 3). Accordingly, *responsiveness* and *responsibility* focus on the entity, situation, and forum (e.g., Day & Klein, 1987).

Furthermore, accountability is associated with *explainability* and *explicability* (Abdul et al., 2018; Thiebes et al., 2021). *Explainability* and *explicability* describe the need to explain an IS and are sufficient conditions to justify oneself for the IS. In addition, *explainability* and *explicability* are essential to make informed decisions (Thiebes et al., 2021). Informed decisions are crucial to minimize potential harm to AI users. In addition, the concepts are necessarily linked to *responsibility*, as *explainability* determines who can be held responsible for what (Thiebes et al., 2021). Thus, *explainability* and *explicability* focus on the criteria arising from the trigger to decide on possible sanctions (e.g., Day & Klein, 1987).

Explainability requires *transparency* and is often used as a synonym for accountability (Bovens, 2007; Thiebes et al., 2021). *Transparency* makes it apparent who can be held accountable for what and why. Thus, disclosing facts can identify the reason for harm (Bovens, 2007). Therefore, *transparency* goes beyond *explainability* and sheds light on how to explain something. Following this, *auditability* is associated with accountability (High-Level Expert Group on Artificial Intelligence, 2019). *Auditability* addresses traceability, whereby how and why harm occurred can be understood. In the context of accountability, *auditability* is crucial because it must be proven that its harm resulted from a specific action (High-Level Expert Group on Artificial Intelligence, 2019). Like the terms *explainability* and *explicability*, *transparency* and *auditability* support the facet of the criteria (e.g., Day & Klein, 1987).

Last, *liability* and *integrity* are associated with accountability (Bovens, 2007; Jobin et al., 2019). *Liability* addresses legal aspects in the context of accountability (Jobin et al., 2019). Thus, *liability* reinforces the legal framework through rewards and sanctions. This happens against the backdrop of *integrity*, which must be present to enforce legal *liability* (Jobin et al., 2019). As a result, *liability* and *integrity* strengthen the facets of trigger, entity, and sanction (e.g., Day & Klein, 1987).

As a result, various terms can be derived from the literature associated with accountability or are already used as synonyms. Due to the dilution of the term accountability, the combination – accountability in the context of AI – gets diluted, unclear, and fuzzy. Therefore, a consistent view of accountable AI is absent from the literature perspective.

Method

To examine the meaning of accountability in the context of AI, we created a corpus of titles and abstracts from 19,978 English-language papers. For this, we used the synonyms and similar terms to accountability derived from the literature to perform a Web of Science query. In addition to the synonyms of and similar terms to accountability, we extended the Web of Science query to include AI techniques such as *machine learning*, *supervised learning*, *unsupervised learning*, *reinforcement learning*, *deep learning*, and *neural networks,* which we gained from previous IS research (Kahdan et al., 2022). We used the following search string for the Web of Science query:

> *TS = ((“artificial intelligence” OR “machine learning” OR “neural network” OR “deep learning” OR “reinforcement learning” OR “supervised learning” OR “unsupervised learning”) AND (“accountab*” OR “responsi*” OR “explainab*” OR “explicab*” OR “transparency” OR “liab*” OR “auditability” OR “integrity”))*

For the data collection, we used the Web of Science core collection. Additionally, we filtered the period 1992-2022 to examine at least 30 completed years following similar bibliometric research about ethical AI (e.g., Kahdan et al., 2022). The corpus from titles and abstracts includes 19,978 English-language papers (query date: 01/01/2023). For IS research analysis, we created another corpus with 3,099 English-language papers. Therefore, we filtered the original corpus to the Web of Science category *Computer Science Information Systems* to create this subsample. To check the validity of the query, we manually examined the paper's relevance according to accountability in the context of AI using a small random subsample of 200 papers.

Consistent with previous research (e.g., Kahdan et al., 2022; Wamba et al., 2021; Zhang et al., 2021), our analysis included four steps based on the three W- and one H-question raised: (1) First, we examine the relevance of accountability in the context of AI in the literature. Using a descriptive approach, we reveal a trend in the literature (since **when** does research consider accountable AI?). (2) Next, we use state-of-the-art technologies to identify the semantically closest words to accountability in the context of AI using Word2Vec word embeddings (Mikolov et al., 2013). We draw conclusions about which terminological subclusters of accountability are formed in the context of AI (**what** does accountable AI mean in research?). (3) In the third step, we identify the effects of interdisciplinary research on IS research. We again use a descriptive approach (Krzywinski et al., 2009) based on citations used to capture the effects of interdisciplinary research (**whereof** is accountable AI affected?). (4) We conclude the examination with a co-occurrence analysis (van Eck & Waltman, 2018). By doing so, we extract terms often used together in titles and abstracts. Thus, we conclude the relevance of specific topics (**how** does IS research use accountable AI compared to interdisciplinary research?).

Results

Trend Analysis – WHEN

We use a descriptive approach with the metadata available in our corpus to answer the question of **when** accountable AI is focused on by research. In doing so, we provide information on whether there is a temporal and spatial trend. Such a trend can provide insight into cultural and legislative differences based on time and space. Accountability in the context of AI has primarily experienced steady growth since 1992. Figure 1 shows the number of publications per year that deal with accountability in the context of AI and indicates an exponential growth of publications since 2013. This exponential growth reflects the current high relevance of this topic (e.g., Adam, 2022; Jobin et al., 2019; Schmidt et al., 2023).

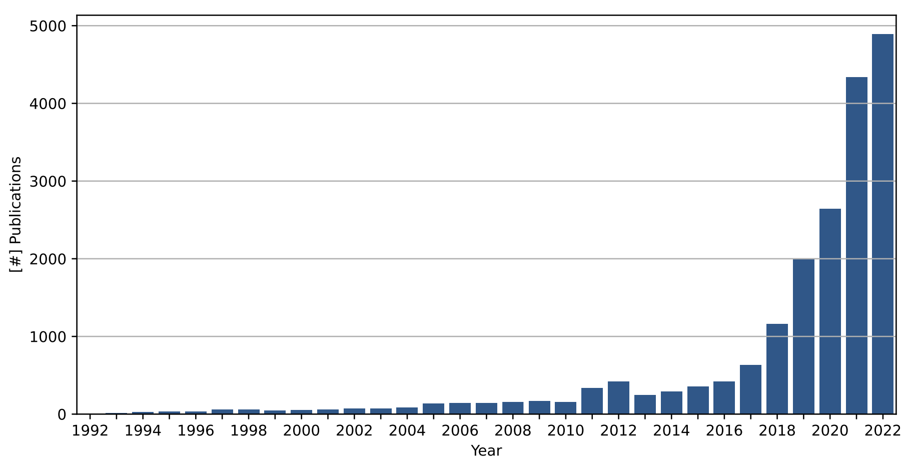


Figure 1. Number of Publications per Year Since 1992

In addition, a geographical trend is observable. China, England, Germany, India, and the USA are the top five countries with the most publications about accountability in the context of AI, having an overall percentage of 65% of the publications. Figure 2 shows the percentage share of the top five countries from 1992 to 2022. We observe that research about accountability in the context of AI took first place in the USA.

At the same time, the topic gained popularity in Europe (England and Germany), but the number of publications in this period was minimal (compare Figure 1). Since 2006, countries from the Asian region (China and India) have emerged as additional scientific contributors and dominate the literature on this topic with 50% in 2022. Due to the even distribution of the literature across different geographical areas, accountability in the context of AI is subject to culturally diverse consideration. Accordingly, different cultural views and impulses in the research area are possible, which are not considered in current definitions and understandings (e.g., Novelli et al., 2023; Wieringa, 2020).

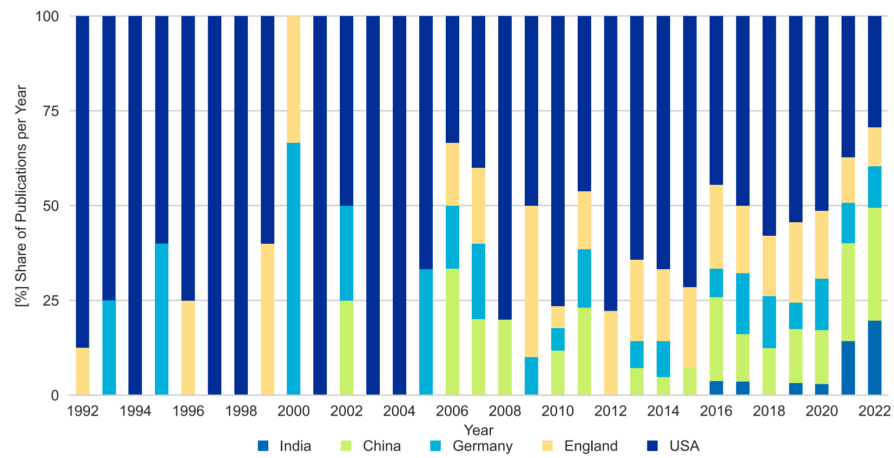


Figure 2. Share of the Top Five Countries with the Highest Number of Publications per Year Since 1992

Similarity Analysis – WHAT

To answer the question of **what** accountability means in the context of AI in research, we use a state-of-the-art approach to create Word2Vec word embeddings (Mikolov et al., 2013) using the abstracts from our corpus. To create Word2Vec word embeddings, we first preprocessed the abstracts. In doing so, we divided the abstracts into lemmatized tokens. Then, we lower-cased the tokens and removed stop words, punctuations, and numbers. For the preprocessing, we used the pre-trained *en_core_web_sm* model from the library *spacy* (Honnibal & Montani, 2017) together with *python* (van Rossum & Drake, 2009). Finally, we used the preprocessed abstracts to create the word embeddings. Therefore, we converted the 53,360 unique lemmatized tokens from the abstracts into word embeddings with vector length $|\vec{v}| = 300$. To bring the created word embeddings to a more analyzable dimension, we used the t-distributed stochastic neighbor embedding (TSNE) representation from the *python* library *sklearn* (Pedregosa et al., 2011). TSNE allowed us to analyze the vectors in a two-dimensional space, and we formed semantic clusters around accountability in the context of AI. Figure 3 shows the schematic representation of the three clusters formed based on the top nine semantically closest words to accountability.

Cluster A (i.e., the technical understanding with its concerns) covers a technical understanding of accountability in the context of AI. In particular, cluster A covers the concerns that accountability is supposed to address, which can arise particularly from a lack of fairness (e.g., Dastin, 2022; Obermeyer et al., 2019). These concerns coincide with the need to justify one's behavior to others (Tetlock, 1985; Wieringa, 2020), as they need to be justified. Cluster B (i.e., ethical and legal aspects) addresses the ethical and legal aspects of accountability in the context of AI. Thus, this cluster meets the foundation of deciding on possible rewards and sanctions resulting from accountability (Bovens, 2007; Wieringa, 2020). Finally, Cluster C (i.e., societal implications) encompasses the effects of accountability in the context of AI on society. Potential harms for which someone has to justify themselves to others thus come into focus. In sum, the three clusters result in addressing the facets of trigger (Cluster A), forum (Cluster B), criteria (Clusters A and B), and sanction (Cluster C) (e.g., Day & Klein, 1987). Entity and situation only indirectly find a place within the three clusters formed and, therefore, are not closely associated with accountability in the literature, leading to a deviation from existing definitions and understandings.

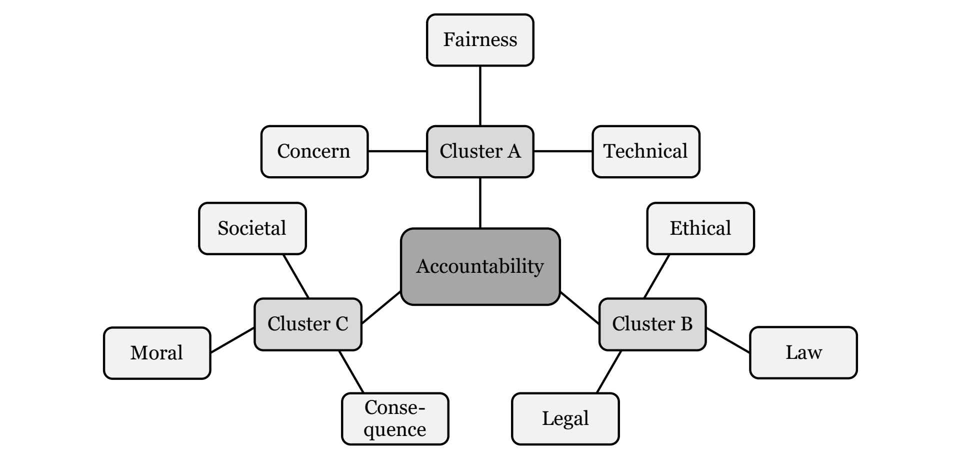


Figure 3. Formed Cluster Using the Word2Vec Representation

To further understand the three clusters formed, Table 1 shows the breakdown of the top nine semantically closest words to accountability in the context of AI, which allows us to understand and interpret the words themselves in more detail. As a result, a clearer sense of the semantic meaning of each of the three clusters formed, and the semantic meaning of accountability emerged. Therefore, we again used the self-created Word2Vec word embeddings to access the semantically closest words.

The breakdown of the words shows that they are closely intertwined: While elements of cluster B reference clusters A and C, and elements of cluster A also reference clusters B and C, this result cannot be confirmed for cluster C, as it misses a semantic connection to cluster A. The missing semantic connection shows that clusters A and B align with cluster C. This alignment demonstrates the relevance of cluster C, making accountability in the context of AI particularly relevant in this sense (i.e., societal, moral, and consequences). In general, due to the close connection of the clusters, we observe a triangular relationship between different perspectives on accountability in the context of AI, which differs from previous definitions that are based on a bipartite relationship (e.g., Horneber & Laumer, 2023; Wieringa, 2020).

	Word	**Semantically Closest Words**					
A	concern	issue	barrier	dilemma	societal	raise	consequence
	fairness	trustworthiness	accountability	algorithmic	epistemic	comprehensibility	definition
	technical	ethical	legal	algorithmic	perspective	socio	sustainability
B	ethical	legal	ethic	moral	technical	normative	algorithmic
	law	legal	regulation	agency	enforcement	legislation	personhood
	legal	ethical	law	moral	ethic	normative	personhood
C	societal	socio	political	rais	institutionalization	digitalization	ramification
	moral	agency	legal	morality	ethical	mind	personhood
	consequence	harm	societal	danger	unintended	crisis	harmful

Table 1. Breakdown of the Semantically Closest Words of the Three Clusters Formed

Dependency Analysis – WHEREOF

We performed a descriptive analysis of the citations used to determine **whereof** accountability is affected. For this purpose, we traced the citations back to their Web of Science categories. Overall, our corpus contained 249 different Web of Science categories, and we manually reduced these categories to 14 overarching clusters by summarizing fine-grained categories. The aggregation allowed us to represent the effects of interdisciplinary research better. Figure 4 shows the effects of interdisciplinary research on other research areas (Krzywinski et al., 2009). For simplified visualization, we removed the reference of a scientific area to itself, contrary to standard practice. Therefore, the unfilled spaces in Figure 4 represent the use of publications of the own scientific area.

Figure 4 shows that the research areas of IS, computer science, natural science, engineering, and medicine publish about accountability in AI. These research areas are closely intertwined and use each other's literature equally. While computer science, natural science, engineering, and medicine draw almost one-third of the literature from their scientific areas, the percentage in IS research is small. Instead, IS research draws primarily from computer science and, almost equal proportions, from natural science, engineering, and medicine. Using non-IS research frequently indicates that interdisciplinary research carries established understandings into IS research. Accountability in the context of AI is thus not shaped by IS research itself but by interdisciplinary research.

In particular, the effect of psychology stands out: While psychology itself is not much concerned with accountability in the context of AI, it has significant effects on medicine and computer science. A clear tendency from **whereof** accountability in the context of AI in IS research is affected is impossible to derive by the proportionate equal distribution of interdisciplinary research. However, based on the analysis, no separate understanding has yet been established or used in IS research.

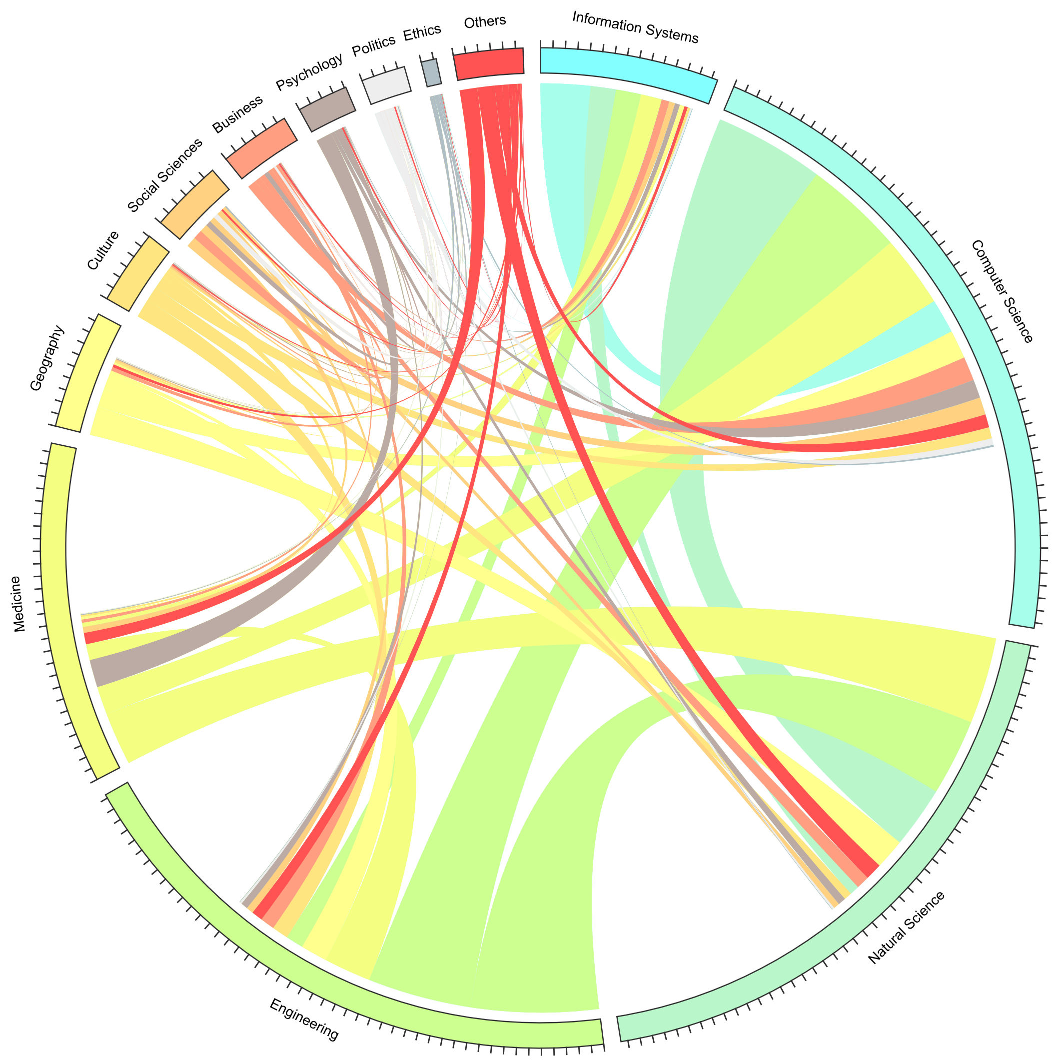


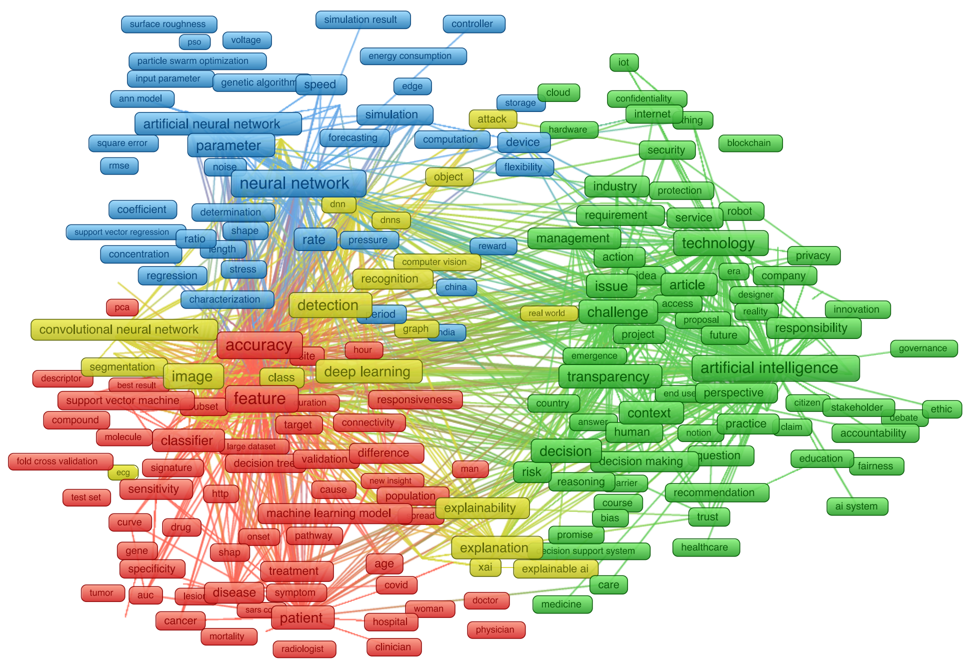
Figure 4. Use of Literature from Interdisciplinary Research
(Ticks per 100 Publications; Relations in Percentage)

Co-Occurrence Analysis – HOW

Analysis Across Interdisciplinary Research

We build a subsample of our dataset by subtracting all IS-related titles and abstracts to differentiate between IS and interdisciplinary research. For calculating the co-occurrences for the analysis, we used binary counting. Due to the large corpus, we minimized the occurring terms by increasing the minimum number of term occurrences from 10, the default value, to 75. Therefore, we reduced our corpus to 938 words for a manageable analysis. Following standard practice, subsequent selection of the top 60% of terms reduced the number of terms for analysis to 563. Figure 5 shows the four automatically resulting clusters formed across interdisciplinary research. The figure visualizes only the most essential terms with the most connections.

Through the connections, four thematically similar clusters are formed across interdisciplinary research: The green cluster describes AI from the user's perspective with their challenges and problems, the red cluster represents medical AI, the blue cluster covers AI techniques and measurements, and the yellow cluster addresses explainable AI and image recognition. We describe the clusters in detail below.



Green: AI from the user perspective with their challenges and problems, Red: medical AI,
Blue: AI techniques and measurements, Yellow: explainable AI and image recognition

Figure 5. Result of the Analysis Across Interdisciplinary Research

The green cluster represents AI from the user's perspective with their challenges and problems. The most important terms are *artificial intelligence*, *challenge*, *human*, *issue*, *technology*, *transparency*, *responsibility*, *risk,* and *user*. *Artificial intelligence* is at the cluster's center and is associated with various challenges and problems. By only referring to the challenges and problems, this cluster takes a meta-perspective on AI without describing and elaborating on them in more detail. The strong connection between *artificial intelligence* and *user* and *human* suggests a clear orientation towards whom the challenges and problems are important. The green cluster offers intersections mainly through transparency to the yellow and red clusters. Thus, the green cluster introduces the user perspective toward explainable AI practices in the medical domain and the challenges within AI techniques and their application models.

The red cluster represents medical AI. The most important terms are *accuracy*, *disease*, *drug*, *feature*, *machine learning model*, *patient*, and *sensitivity*. Thus, the red cluster covers a specific application area where accountability is used in the context of AI. The cluster points to the application context through *disease*, *drug,* and *patient*. It simultaneously emphasizes the prerequisites for using AI-based systems in the medical context. These prerequisites are represented by the terms *accuracy*, *feature*, and *sensitivity* and impose requirements on the used *machine learning models*. Accordingly, the red cluster is intensely focused on the high criticality of AI-based systems when used within the medical context. Connections to the blue cluster occur through technical requirements such as *accuracy* and *features*, while *patient* and *disease* connect it to the yellow cluster. The connections to the yellow cluster show that explanations in the medical context are essential because the terms *explainability* and *explanation* predominate.

The blue cluster represents AI techniques and measurements. The most important terms are *coefficient*, *neural network*, *parameter*, *rate*, *regression*, *simulation*, and *speed*. *Neural network* represents the center of the very dense cluster and primarily connects to AI measurements. In addition, other occurring terms in this cluster about AI techniques, such as *regression,* highlight a very technically focused cluster. Due to the broad technical focus of AI techniques and measurements, the blue cluster is closely connected to all other clusters. Importantly, *neural network* has the most connections to other clusters. However, these are primarily *challenges*, *issues*, and *human* encounters in the green cluster. Therefore, *neural networks* emphasize the challenges from the user's perspective.

The yellow cluster represents explainable AI and image recognition. The most important terms are *deep learning*, *detection*, *explainability*, *explanation*, *image*, and *segmentation*. While the green, red, and blue clusters are centered, the yellow cluster is widely scattered among the three clusters. Thus, this cluster has an intersection function, representing the explainable AI perspective between the user perspective and the medical context and the intersection between image recognition with *neural networks* for the medical context. The cluster is aligned closer to the red and blue clusters rather than the green cluster. This emphasizes the focus on image recognition and shows that recognizing images requires particular forms of *neural networks*. Therefore, *neural networks* are subject to new measurements and application areas in the medical context.

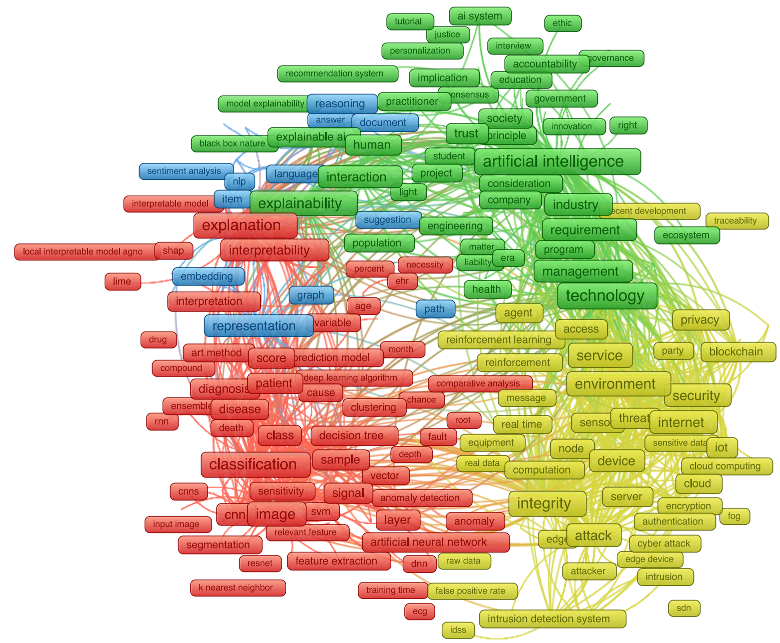
Analysis of IS Research

Analogous to the analysis across interdisciplinary research, we performed the co-occurrence analysis for IS research (corpus only with IS research). However, we reduced the thresholds for the minimum term occurrences from 75 to 15 because our corpus of 3,099 English-language papers is smaller than the original corpus. Thereby, 981 terms fulfill the minimum number of term occurrences, so we compared almost the same amount of terms in each analysis. By selecting the top 60% of the most important terms, we obtained 589 terms for analysis. Thus, we considered a comparable number of unique terms in the analysis across IS and interdisciplinary research.

Figure 6 shows the resulting four clusters formed: The blue cluster focuses on natural language processing, the green cluster represents social and human-centric dimensions of AI, the red cluster covers AI development, medical AI, and explainable AI, and the yellow cluster addresses the application context of IT security. We describe the clusters in detail below.

The blue cluster represents a focus on natural language processing. The most important terms are *embedding*, *knowledge graph*, *language*, *natural language processing*, *representation*, and *text*. The thematic cluster does not center on any particular topic. Instead, the cluster is strongly mixed with the green (social and human-centric dimensions) and red clusters (AI development, medical AI, and explainable AI). Thus, we obtain the blue cluster as an intersection between the two clusters. Nevertheless, forming a separate semantic cluster suggests an independent, additional cluster is being developed. This assumption is supported by the growing examination of chatbots built on the AI technique of natural language processing (Schanke et al., 2021; Vassilakopoulou et al., 2022). A clear separation from other thematic clusters is not yet observable, so this cluster draws heavily on concepts from the other two. Thus, a clear directional development of accountability in the context of AI is not yet identifiable.

The green cluster represents the social and human-centric dimensions. The most important terms are *artificial intelligence*, *benefit*, *human*, *interaction*, *management*, *responsibility*, *requirement*, and *technology*. We observe a strong distortion along the red and yellow clusters. While *interaction* and *human* are closely related to the red cluster, terms like *management* and *technology* are thematically close to the



Green: Social and human-centric dimensions of AI, Red: AI development, medical and explainable AI,
Blue: Natural language technology, Yellow: Application context of IT security

Figure 6. Result of the Analysis of IS Research

yellow cluster. *Artificial intelligence* is at the center of the cluster and connects both edges. The cluster distortion indicates that the social and human-centered dimensions are examined once more from the technological or human-computer interaction perspectives. For the consideration of accountability in the context of AI, the green cluster is of much interest as it highlights the dichotomy between human- and computer-oriented investigation.

The red cluster represents three subclusters (i.e., AI development, medical AI, and explainable AI). The most important terms are *classification*, *classifier*, *convolutional neural network*, *diagnosis*, *disease*, *explainability*, *explanation*, *image*, *interpretability*, and *patient*. Terms like *classification*, *classifier*, *convolutional neural network*, and *image* represent the center of the AI development cluster. The AI development cluster connects the red cluster with the yellow cluster. Thematically closer to the blue and green cluster is medical AI. Terms such as *diagnosis*, *disease*, and *patient* characterize the subcluster. It is self-contained and has only a few connections to other thematic clusters. The third subcluster, located in the center of the blue cluster, focuses on explainable AI. The terms like *explainability*, *explanation*, and *interpretability* describe it. Furthermore, it has a solid connection to medical AI. At the same time, this subcluster forms the intersection of the blue and green clusters. The red cluster thus has a large number of technical facets that are relevant to the development of AI-based systems. For accountability in the context of AI, the red cluster represents relevant application areas where accountability is considered or used.

Finally, the yellow cluster represents the application context of IT security. The most important terms are *attack*, *device*, *environment*, *integrity*, *internet of things*, *intrusion detection system*, *privacy*, *security*, and *service*. While the term *environment* forms the cluster's center, *integrity* thematically connects the green and red clusters. However, due to the distance between *environment* and *integrity*, a thematic distance between the two terms appears. Nevertheless, the yellow cluster is firmly centered and self-contained. Most of the impulses come from the green cluster, which indicates a more pronounced user perspective than a technology-centric consideration of IT security. The distinctive cluster demonstrates particular attention to accountability in the context of AI in this application context.

Commonalities and Differences Across IS and Interdisciplinary Research

The previous two subsections have isolated considered interdisciplinary from IS research, and we can compare the two results as we were using the same proportional threshold of the minimum number of term occurrences. Comparing these two results and how different perspectives and thematic directions are of great interest indicating whether IS research follows interdisciplinary research or moves into its research directions.

The comparison reveals that IS research is highly centered and thematically close compared to interdisciplinary research. This highly centered and thematically close structure illustrates that IS research has a very focused view on accountability in the context of AI. Additionally, IS and interdisciplinary research both have four clusters formed, with red (i.e., medical AI vs. AI development, medical AI, and explainable AI) and green (i.e., AI from the user perspective with its challenges and problems vs. social and human-centric dimensions of AI) clusters having a substantial overlap. Both clusters are strongly connected to each other, suggesting the same topics of interest in IS and interdisciplinary research. While they address the same main topics, the clusters differ in whether explainable AI is a thematic subfield of those clusters or not. The findings indicate that IS research develops application-specific solutions because explainable AI focuses on AI development and medical AI within the red cluster. This insight is contrasted by interdisciplinary research, where explainable AI is located in other clusters, showing that explainable AI is addressed more generalized and without any application-specific solutions. As a result, IS and interdisciplinary research covers the same topics but differ in the specialized consideration of explainable AI, making IS research more application-focused.

The most significant differences appear in the blue and yellow clusters (i.e., AI techniques and measurements, explainable AI and image recognition vs. natural language processing, IT security). These clusters have different thematic meanings in both considerations. While the blue cluster addresses AI techniques and measurements, and the yellow cluster covers explainable AI and image recognition in interdisciplinary research, the blue cluster in IS research focuses on natural language processing, and the yellow cluster addresses the application context of IT security in IS research. Therefore, these four clusters differ and indicate a separation between IS and interdisciplinary research, comparing each cluster from IS to interdisciplinary research. While interdisciplinary research focuses on a broad view of AI-based systems, which more research directions within interdisciplinary research might explain, IS research examines specific application contexts such as natural language processing and IT security. As a result, IS research sets accountability in the context of AI in specific contexts and tries to find specialized solutions for problems arising when using AI-based systems in those contexts. This comes at the cost of a more generalized consideration of accountability in the context of AI, making the construct challenging to adapt in other contexts. Therefore, IS research has unused potential to examine accountability in the context of AI more broadly, following interdisciplinary research.

Discussion

This study investigated the origin and development of accountability in the context of AI in research. Therefore, we raised three W- and one H-question. Thereby, various theoretical methods, ranging from descriptive approaches to state-of-the-art Word2Vec word embeddings (Mikolov et al., 2013), brought transparency into the unclear and fuzzy understanding of accountability in the context of AI. Analyzing publications per year and geographical distribution allowed us to answer the first W-question (**when**). We observed primarily exponential growth, and primarily, American, European, and Asian regions currently consider the topic. The Word2Vec word embeddings created by the abstracts gave us a clearer picture of what semantic meaning accountability has in the context of AI in research. During this process, we identified three clusters pointing toward the technical solution, the ethical and legal aspects, and the effects of accountability in the context of AI. Thus, we addressed the second W-question, **what** accountability means in the context of AI in research. To answer the last W-question (**whereof**), we examined the origins of citations used (Krzywinski et al., 2009). Here, we could not identify a clear tendency from where accountability in the context of AI in IS research gets affected. The most common references in IS research come from natural and computer science. However, in our analysis, we found that IS research references itself less frequently, so we assume that an understanding of accountability in the context of AI has not yet been established or used, while definitions already exist in IS research (e.g., Horneber & Laumer, 2023; Novelli et al., 2023; Wieringa, 2020). To answer the raised H-question (**how**), we used co-occurrences to compare IS with interdisciplinary research (van Eck & Waltman, 2018). We derived that IS research differs from interdisciplinary research in considering explainable AI and focusing on specialized application contexts. In contrast, interdisciplinary research takes a broader view of accountability in the context of AI.

Contributions to Research and Practical Implications

Given the need for a definition and shared understanding of accountability in the context of AI, this study contributes to IS research on accountable AI and practitioners by answering the three W- and one H-question posed (i.e., **when**, **what**, **whereof**, and **how**).

Temporal and Geographical Relevance of Accountability in the context of AI

First, we indicate a geographic shift in the literature from the Anglo-American to the Asian region when considering accountability in the context of AI. Accordingly, cultural and legislative differences are prevalent, which are not considered by existing and already used definitions and understandings of accountability (e.g., Adam, 2022; Vance et al., 2013, 2015; Wieringa, 2020). The missing consideration is problematic because accountability, through all reviewed definitions, consistently focuses on acting morally and ethically by having individuals justify their actions and behaviors (e.g., Adam, 2022; Tetlock, 1985; Vance et al., 2013, 2015; Wieringa, 2020). Any cultural and legislative differences may ensure that other regions' moral and ethical orientation requires a more profound or less in-depth focus on such justification and moral and ethical behavior. Accordingly, IS research must incorporate and constantly challenge these moral and ethical differences in light of culture and legislature when considering accountability in the context of AI. Alternatively, IS research could include cultural and legislative dimensions in the definition and understanding of accountability in the context of AI. However, this poses significant challenges to IS research reconciling accountability's ethical and moral construct with cultural and legislative dimensions. If appropriate, it would be possible to create multiple definitions of accountability in the context of AI that apply to specific cultures and legislation. Nevertheless, creating multiple definitions comes at the risk that the understanding of accountability in the context of AI will be diluted again and that no new clarity about the fuzzy and unclear concept will emerge. Therefore, IS research is encouraged to create and commit to one shared understanding of accountability in the context of AI, which applies to all cultures and legislation.

Understanding of Accountability in the context of AI

Second, we demonstrate that three semantic topics around accountability in the context of AI have emerged over time (i.e., (1) technical understanding with its concerns, (2) ethical and legal aspects, and (3) societal implications). While previous research in earlier definitions and understandings assumes six dimensions (Day & Klein, 1987) or a relationship between actors and forums (Bovens, 2007; Novelli et al., 2023; Wieringa, 2020), we derive a tripartite structure from the literature. As a result, existing definitions and understandings of accountability in the context of AI are not supported by the use in the literature. IS research has the opportunity to follow this tripartite structure trend in the literature based on knowledge accumulated over a decade, but this would cause conflicts with newer definitions as they apply to bipartite structure in terms of the relationship between actors and forums (Bovens, 2007; Novelli et al., 2023; Wieringa, 2020). Nevertheless, an orientation towards a tripartite structure is helpful for IS research since the creation of newer definitions through structure literature reviews covered the depth but not the necessary breadth. Therefore, the task of IS research is to reconcile the breadth presented here, through the identified semantic synonyms, with the depth already provided by structured literature reviews (e.g., Wieringa, 2020). This is important to get a more comprehensive picture of accountability in the context of AI in IS research. Having a more comprehensive picture of IS research helps IS research be more accurate and usable in studying accountability in the context of AI in different IS domains.

Effect of Interdisciplinary Research on Accountability in the Context of AI

Third, we show that IS research mainly uses and is oriented toward literature from interdisciplinary research. This orientation is comprehensible because accountability is, at its essence, a legal, moral, and ethical understanding that needs to be incorporated into IS research (e.g., Bovens, 2007; Tetlock, 1985; Wieringa, 2020). Accordingly, deciding what IS research orientates toward is crucial because the consideration of accountability in IS research is still in its early stages (e.g., Adam, 2022; Horneber &

Laumer, 2023; Schmidt et al., 2023). This allows IS research to draw clear boundaries on how accountability in the context of AI should be understood, so a dilution of the understanding, like in other scientific areas, can be counteracted early (e.g., Mulgan, 2000). To draw clear boundaries is essential because we can already equate and derive eight different terms and synonyms of accountability. IS research, therefore, still has the chance to constrain accountability in the context of AI strongly but, at the same time, must manage the balancing act between being too restrictive and too liberal in definition and understanding. If IS research is too liberal, there is a risk that accountability in the context of AI could be continuously interpreted and understood differently. This is problematic because accountability is already a fuzzy and unclear construct, which makes the comparability of different study results questionable. As a result, we emphasize the importance of establishing exactly one definition with sufficient depth and breadth for accountability in the context of AI within IS research. Following this, all researchers would discuss the same topic and construct. Therefore, a shared definition and understanding across IS research is essential to promote dialogue within IS research and to counteract a dilution of accountability in the context of AI. In this light, IS research's lack of internal referencing should be explored more closely regarding the causes of why IS research does not focus on their scientific area but relies on other areas. This would shed light on what IS research should do to achieve a more focused study of accountability in the context of AI.

Accountability in the Context of AI, an Ever-Expanding Understanding?

Fourth, we reveal that four thematic clusters have formed around accountability in the context of AI in IS research. By matching IS and interdisciplinary research, we demonstrate that IS research differs from previous interdisciplinary research in two thematic clusters. Combined with using literature from interdisciplinary research, the substantial divergence of thematic clusters is critical because accountability in the context of AI addresses different topics. Accordingly, definitions and understandings of accountability carried into IS research must be critically questioned and tailored to fit. This is particularly evident in the deviations of the clusters with natural language processing and IT security. Only through the special adaptation of accountability in these topics IS research can meet and satisfy its questions. By adopting specialized definitions and understandings from interdisciplinary research, the exact fit of these contexts must be challenged. This finding helps IS research as it must continue to break away from interdisciplinary research and practice its own idea of accountability in the context of AI. We believe this is the best way to ensure that accountability in the context of AI continues to be anchored in IS research through a joint dialogue across researchers.

Coverage of Accountability in the Context of AI as a Challenge for Practice

Besides our contributions to research, our study offers an important practical implication. By creating transparency about accountability in the context of AI, we highlight which topics accountability addresses. The transparency gained should interest companies and policymakers significantly, as accountability is becoming increasingly important due to the planned EU AI Act or the proposed US algorithmic accountability act of 2022 (117th Congress USA, 2022; European Commission, 2021). Where and in which forms accountability occurs in the context of AI allows conclusions to be drawn about what companies must consider when developing AI-based systems. In particular, we bring attention to issues related to accountability in the context of AI. As a result, we illustrate that when implementing and operating AI-based systems, accountability in the context of AI should not be considered in isolation but in combination with other aspects. In particular, we highlight the diversity of facets around accountability in the context of AI. Companies have already established self-developed guidelines and an understanding of accountability in the context of AI (e.g., IBM (2022), Microsoft Corporation (2022), Google: Pichai (2018)). However, the established guidelines only cover the many aspects and requirements of accountability in a fragmented way. Therefore, the practice should focus more on the findings and understanding of the literature. This awareness is crucial to ensure adequate accountability coverage in the context of AI in practice. Such adequate clarification of accountability is also important for creating appropriate guidelines for developing accountable AI-based systems. We believe that accountable AI-based systems would contribute to the more ethical use of such systems and might contribute to more trust regarding AI-based systems, which threaten workers of losing their jobs (e.g., Goldberg, 2023).

Limitations and Further Research

The following limitations provide starting points for future research. First, our study highlights the urgent need for IS research to adjust a definition and a shared understanding of accountability in the context of AI in specific ways. However, due to the methodology chosen in our study, this study can only point out the need and the needed directions but cannot revise existing definitions. Therefore, future research must use other methodologies like supplementary content analyses to generate in-depth insights and to adjust such a definition and shared understanding. However, our findings are essential, suggesting necessary aspects, such as the geographic shift and the three different semantic meanings. Thus, this study can already provide foundations for following IS research. Second, we only used Web of Science for our analysis, making our corpus dependent on only one database. Adding other databases, such as Scopus (`scopus.com`), would allow us to obtain a higher coverage of the literature (Mongeon & Paul-Hus, 2016). Therefore, we limited the attendance to the scientific consideration of accountability in the context of AI. As a result, we found that the topic area is already understood and addressed in a very controversial way in literature. Using additional data sources such as forum discussions, newspaper articles, or social media platforms may contribute to a better understanding of accountability in the context of AI in practice, as the corpus would become more extensive and have a higher variance of perspectives on this topic. Third, we created Word2Vec word embeddings for similarity analysis using our corpus. Since the number of words in our corpus is relatively small, with titles and abstracts of 19,978 English-language papers, the word embeddings have low robustness. Future research might use full publications in addition to titles and abstracts to access more data. Additionally, instead of using the state-of-the-art approach through Word2Vec word embeddings, classical analysis methods such as Levenshtein distance can be used. Differences in similarity can be highlighted and elaborated on to increase the robustness of Word2Vec word embeddings. The similarities between the different analysis methods can further increase the robustness of the statement of what accountability in the context of AI means. Fourth, co-occurrences only show the absolute occurrence of connections between two terms. Accordingly, recent literature and research streams become visible only with a time lag. By overweighting recent literature, subsequent studies can counteract this time lag, but this study already shows differences between IS and interdisciplinary research. Finally, we have conducted a snapshot-based view of the literature, which only allows us to interpret accountability in the context of AI at present and provides only a small short-term forecast. Performing dedicated analyses per year can gain more precise insights into which sub-aspects of accountability were particularly crucial in the context of AI. Temporal trends can thus be better identified and contribute to more transparency. Nevertheless, our study already sheds light on a fuzzy term that is difficult to narrow down in interdisciplinary and IS research.

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References

117th Congress USA. (2022). *H.R.6580 - Algorithmic Accountability Act of 2022*. Retrieved 02/24/2023 from https://www.congress.gov/bill/117th-congress/house-bill/6580/text

Abdul, A., Vermeulen, J., Wang, D., Lim, B. Y., & Kankanhalli, M. (2018). *Trends and Trajectories for Explainable, Accountable and Intelligible Systems: An HCI Research Agenda* Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems,

Adam, M. (2022). *Accountability-Based User Interface Design Artifacts and Their Implications for User Acceptance of AI-Enabled Services* European Conference on Information Systems, https://aisel.aisnet.org/ecis2022_rp/5

Adam, M., Roethke, K., & Benlian, A. (2022). Human Versus Automated Sales Agents: How and Why Customer Responses Shift Across Sales Stages. *Information Systems Research*, *0*(0), 1-21.

Asatiani, A., Malo, P., Nagbøl, P. R., Penttinen, E., Rinta-Kahila, T., & Salovaara, A. (2020). Challenges of explaining the behavior of black-box AI systems. *MIS Quarterly Executive*, *19*(4), 259-278.

Batey, M. V., & Lewis, F. M. (1982). Clarifying Autonomy and Accountability in Nursing Service: Part 1.

Journal of nursing administration, *12*(9), 13–18.
Berente, N., Gu, B., Recker, J., & Santhanam, R. (2021). Managing Artificial Intelligence. *MIS Quarterly*, *45*(3), 1433–1450.
Berger, B., Adam, M., Rühr, A., & Benlian, A. (2021). Watch Me Improve - Algorithm Aversion and Demonstrating the Ability to Learn. *Business & Information Systems Engineering*, *63*(1), 55–68.
Bovens, M. (2007). Analysing and Assessing Accountability: A Conceptual Framework. *European Law Journal*, *13*(4), 447–468.
Choi, T. J., & Valente, M. (2022). The Crisis in Local Newspapers and Organizational Wrongdoing: The Role of Community Social Connectedness. *Organization Science*, *0*(0).
Citron, D. K., & Pasquale, F. (2014). The Scored Society: Due Process for Automated Predictions. *Washington Law Review*, *89*, 1–33.
Collins, C., Dennehy, D., Conboy, K., & Mikalef, P. (2021). Artificial intelligence in information systems research: A systematic literature review and research agenda. *International journal of information management*, *60*, 102383. https://doi.org/10.1016/j.ijinfomgt.2021.102383
Cooper, A. F., Moss, E., Laufer, B., & Nissenbaum, H. (2022). *Accountability in an Algorithmic Society: Relationality, Responsibility, and Robustness in Machine Learning* 2022 ACM Conference on Fairness, Accountability, and Transparency,
Dastin, J. (2022). Amazon Scraps Secret AI Recruiting Tool That Showed Bias Against Women. In *Ethics of Data and Analytics* (pp. 296–299). Auerbach Publications.
Day, P., & Klein, R. (1987). *Accountabilities: Five Public Services*. Tavistock Publications.
European Commission. (2021). *Proposal for a Regulation of the European Parliament and of the Council: Laying Down Harmonised Rules on Artificial Intelligence (Artificial Intelligence Act) And Amending Certain Union Legislative Acts*. https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=celex:52021PC0206
Goldberg, E. (2023, 2023/05/23). A.I.'s Threat to Jobs Prompts Question of Who Protects Workers. *The New York Times*. https://www.nytimes.com/2023/05/23/business/jobs-protections-artificial-intelligence.html
Hall, A. T., Frink, D. D., & Buckley, M. R. (2017). An accountability account: A review and synthesis of the theoretical and empirical research on felt accountability. *Journal of Organizational Behavior*, *38*(2), 204-224.
High-Level Expert Group on Artificial Intelligence. (2019). *Ethics Guidelines for Trustworthy AI*. European Commission. Retrieved 12/16/2022 from https://ec.europa.eu/futurium/en/ai-alliance-consultation.1.html
Honnibal, M., & Montani, I. (2017). *spaCy 2: Natural Language Understanding With Bloom Embeddings, Convolutional Neural Networks and Incremental Parsing*.
Horneber, D., & Laumer, S. (2023). Algorithmic Accountability. *Business & Information Systems Engineering*, *1*(1), 1-8.
IBM. (2022). *Accountability*. Retrieved 01/07/2023 from https://www.ibm.com/design/ai/ethics/accountability/
Jobin, A., Ienca, M., & Vayena, E. (2019). The Global Landscape of AI Ethics Guidelines. *Nature Machine Intelligence*, *1*, 389–399.
Jung, D., Dorner, V., Weinhardt, C., & Pusmaz, H. (2018). Designing a Robo-Advisor for Risk-Averse, Low-Budget Consumers. *Electronic Markets*, *28*, 367–380.
Jussupow, E., Spohrer, K., & Heinzl, A. (2022). Radiologists' Usage of Diagnostic AI Systems: The Role of Diagnostic Self-Efficacy for Sensemaking From Confirmation and Disconfirmation. *Business & Information Systems Engineering*, *64*, 293–309.
Kahdan, M., Hartwich, N., & Salge, J. (2022). *Ethical AI Research Untangled: Mapping Interdisciplinary Perspectives for Information Systems Research* ICIS 2022 Proceedings,
Kaur, D., Uslu, S., Rittichier, K. J., & Durresi, A. (2022). Trustworthy Artificial Intelligence: A Review. *ACM Computing Surveys*, *55*(2), 1-38.
Krzywinski, M., Schein, J., Birol, I., Connors, J., Gascoyne, R., Horsman, D., Jones, S. J., & Marra, M. A. (2009). Circos: An Information Aesthetic for Comparative Genomics. *Genome research*, *19*(9), 1639–1645.
Martin, K. (2019). Ethical Implications and Accountability of Algorithms. *Journal of Business Ethics*, *160*, 835–850.
Microsoft Corporation. (2022). *Microsoft Responsible AI Standard, V2*. Microsoft Corporation. Retrieved 01/07/2023 from https://query.prod.cms.rt.microsoft.com/cms/api/am/binary/RE5cmFl

Mikolov, T., Chen, K., Corrado, G., & Dean, J. (2013). Efficient Estimation of Word Representations in Vector Space. *arXiv preprint arXiv:1301.3781*, 1-12.

Min, H. (2010). Artificial Intelligence in Supply Chain Management: Theory and Applications. *International Journal of Logistics Research and Applications*, *13*(1), 13-39.

Mongeon, P., & Paul-Hus, A. (2016). The Journal Coverage of Web of Science and Scopus: A Comparative Analysis. *Scientometrics*, *106*, 213–228.

Mulgan, R. (2000). 'Accountability': An Ever-Expanding Concept? *Public administration*, *78*, 555–573.

Novelli, C., Taddeo, M., & Floridi, L. (2023). Accountability in artificial intelligence: what it is and how it works. *AI & SOCIETY*, *1*, 1-12.

Obermeyer, Z., Powers, B., Vogeli, C., & Mullainathan, S. (2019). Dissecting Racial Bias in an Algorithm Used to Manage the Health of Populations. *Science*, *366*(6464), 447-453.

Pedregosa, F., Varoquaux, G., Gramfort, A., Michel, V., Thirion, B., Grisel, O., Blondel, M., Prettenhofer, P., Weiss, R., Dubourg, V., Vanderplas, J., Passos, A., Cournapeau, D., Brucher, M., Perrot, M., & Duchesnay, E. (2011). Scikit-learn: Machine Learning in Python. *Journal of Machine Learning Research*, *12*, 2825–2830.

Pichai, S. (2018). *AI at Google: Our Principles*. Google. Retrieved 01/07/2023 from https://blog.google/technology/ai/ai-principles/

Raji, I. D., Smart, A., White, R. N., Mitchell, M., Gebru, T., Hutchinson, B., Smith-Loud, J., Theron, D., & Barnes, P. (2020). *Closing the AI Accountability Gap: Defining an End-To-End Framework for Internal Algorithmic Auditing* Proceedings of the 2020 Conference on Fairness, Accountability, and Transparency,

Schanke, S., Burtch, G., & Ray, G. (2021). Estimating the Impact of "Humanizing" Customer Service Chatbots. *Information Systems Research*, *32*(3), 736–751.

Schmidt, J.-H., Bartsch, S. C., Adam, M., & Benlian, A. (2023). *Accountability Incongruence and Its Effects on AI Developers' Job Satisfaction* European Conference on Information Systems, Kristiansand, Norway.

Shin, D., & Park, Y. J. (2019). Role of Fairness, Accountability, and Transparency in Algorithmic Affordance. *Computers in Human Behavior*, *98*, 277–284.

Solomon, B. C., Hall, M. E. K., & Muir, C. P. (2022). When and Why Bias Suppression Is Difficult to Sustain: The Asymmetric Effect of Intermittent Accountability. *Academy of Management Journal*, *65*(5), 1450–1476.

Spiekermann, S., Krasnova, H., Hinz, O., Baumann, A., Benlian, A., Gimpel, H., Heimbach, I., Köster, A., Maedche, A., & Niehaves, B. (2022). Values and ethics in information systems: a state-of-the-art analysis and avenues for future research. *Business & Information Systems Engineering*, *64*, 247-264.

Talbi, E.-G. (2021). Machine Learning Into Metaheuristics: A Survey and Taxonomy. *ACM Computing Surveys*, *54*(6), 1–32.

Tetlock, P. E. (1985). Accountability: The Neglected Social Context of Judgment and Choice. *Research in Organizational Behavior*, *7*, 297–332.

Thiebes, S., Lins, S., & Sunyaev, A. (2021). Trustworthy Artificial Intelligence. *Electronic Markets*, *31*, 447–464.

van Eck, N. J., & Waltman, L. (2018). VOSviewer Manual v1.6.8. In: Universiteit Leiden.

van Rossum, G., & Drake, F. L. (2009). *Python 3 Reference Manual*. CreateSpace.

Vance, A., Lowry, P. B., & Eggett, D. (2013). Using Accountability to Reduce Access Policy Violations in Information Systems. *Journal of Management Information Systems*, *29*(4), 263-290.

Vance, A., Lowry, P. B., & Eggett, D. (2015). Increasing Accountability Through User-Interface Design Artifacts. *MIS Quarterly*, *39*(2), 345-366.

Vassilakopoulou, P., Haug, A., Salvesen, L. M., & O. Pappas, I. (2022). Developing Human/AI Interactions for Chat-Based Customer Services: Lessons Learned From the Norwegian Government. *European Journal of Information Systems*, *32*(1), 10-22.

Wamba, S. F., Bawack, R. E., Guthrie, C., Queiroz, M. M., & Carillo, K. D. A. (2021). Are We Preparing for a Good AI Society? A Bibliometric Review and Research Agenda. *Technological Forecasting and Social Change*, *164*, 1-27.

Wieringa, M. (2020). What to Account for When Accounting For Algorithms: A Systematic Literature Review on Algorithmic Accountability. In *Proceedings of the 2020 Conference on Fairness, Accountability, and Transparency* (pp. 1–18).

Zhang, Y., Wu, M., Tian, G. Y., Zhang, G., & Lu, J. (2021). Ethics and Privacy of Artificial Intelligence: Understandings From Bibliometrics. *Knowledge-Based Systems*, *222*, 1-14.