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TOWARDS A RECONCEPTUALIZATION OF DATA IN ORGANIZATIONS: A LITERATURE REVIEW

Research Paper

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Abstract

Information Systems researchers have sought to demonstrate the strategic value of data in organizations through robust evidence. Over time, the ways data benefit organizations have evolved and become more diverse, yet definitions of data and their value propositions have not kept up and remain disconnected. The field still lacks clear understanding of various roles data play in organizations and how to define them. This paper presents a comprehensive review of related literature in the Information Systems and Management fields from the past two decades. We first conduct a systematic literature search and organize them into key research themes by the purpose of data use. We then propose a reconceptualization of data that takes into account their distinct features. Our aim is to provide an explanation for the unique nature of data and the diverse sources of their value in organizations.

Keywords: Data value, data use, data ontology, data artifacts, data commodity, analytics / AI value.

1 Introduction

Scholars have generally agreed that data possess a diverse and rare value in organizations (Brynjolfsson, Hitt and Kim, 2011; Brynjolfsson and McElheran, 2016; Grover *et al*., 2018; Hagiu and Wright, 2020). Extant research has focused on examining the impact of data on business outcomes (Chen *et al*., 2012; Günther *et al*., 2017; Surbakti *et al*., 2020). However, while the ways data benefit organizations are constantly evolving, definitions and value propositions of data in the literature have not kept up and remain disjointed. For instance, a Delphi study in the field (Zins, 2007) produced over forty different definitions of data. Indeed, scholars argue that discussions of data are "bedevilled by inconsistencies" in how they are defined in the literature (Jones, 2019). Moreover, built upon the premises of IT and IS business value research, data are frequently handled and measured in a manner similar to other IS assets, but this approach now seems inadequate to comprehend the intricate nature of data usage in organizations. Consequently, this situation poses difficulties for both researchers and practitioners in determining and realizing the value of data (Brynjolfsson, Rock and Syverson, 2018; Grover *et al*., 2018). Therefore, we see the need to seek conceptual clarity on what constitutes the value of data, the effect, and the character of the "material" (Zins, 2007) on which this phenomenon is based (Jones, 2019).

In today's business landscape, while recognizing the disruptive impact of data in the digital economy (Baesens *et al*., 2014), many organizations actively seek to utilize data and sustain their competitive advantages (PwC, 2019). However, according to the European Commission, despite vast amounts of data being available, 80% of industrial data are never used (European Commission, 2020). Also, it can be hard for those who drive big data or AI projects inside organizations to articulate the value of their initiatives. According to a survey with data executives representing 67 global companies (Someh, Wixom and Zutavern, 2020), practitioners do not have good use cases that could help demonstrate the value of their data initiatives and link business purposes. There is therefore an urgency for researchers to understand roles data play in organizations to provide guidance to practitioners (Baesens *et al*., 2014; Abbasi *et al*., 2016; Grover *et al*., 2018).

Given this background, we take a step towards synthesizing the prior knowledge, by answering the following research questions: *How does research identify the value of data in organizations? What features of data may be associated with the roles they play?*

To achieve this aim, we conducted a comprehensive review of research articles published in the Information Systems and Management fields over the past two decades. Through our analysis, we extracted key themes that represented the different purposes of data use in organizations. Based on these themes, we argue that a reconceptualization of data is needed, and we do so by considering their distinguishable features.

This research aims to underpin existing literature by providing clarifications of the diverse sources of data value in organizations and the key features identified. It is intended to support research efforts in data value capture and measurement, as well as to enable more purpose-driven use of data in practice.

The remainder of this paper is organized as follows. Following the introduction, Section 2 outlines our review framework, and Section 3 the research methodology. Section 4 presents our research findings with a synthesis of key research themes, and Section 5, our proposed conceptualizations of data and their implications. Finally, we conclude this article with some discussions in Section 6.

2 Theoretical Framework

As we review the value of data in organizations, we regard it important to take a holistic view of the "ensemble" of key enablers: technology (or system), people, and organization (Orlikowski and Iacono, 2001). The dynamic interactions between them drive the business outcomes, "whether during construction, implementation, or use in the organization" (Orlikowski and Iacono, 2001). Hevner *et al*. (2004) also emphasize an interplay between these enablers; "together these define the business need or problem". Further, informed by a causal link between use and performance, Burton-Jones and Straub (2006) conceptualize system usage with key dimensions of the user, system, and/or task. Collectively, these theoretical arguments provide us with an interesting angle to organize our review.

Though extant literature has informed us through several reviews on data value (Günther *et al*., 2017; Surbakti *et al*., 2020; Baecker, Böttcher and Weking, 2021; Klee, Janson and Leimeister, 2021), none of these reviews have used a lens that focuses on the dimensions of use, people, and organization. To provide this holistic view, our review framework includes these dimensions, intending to observe the main actors through value creation from system use to business performance (Benbasat and Zmud, 2003; Burton-Jones and Straub, 2006).

- By "*use*", we aim to investigate not only the "task" (Burton-Jones and Straub, 2006), work processes, and specific instrumentations of data, but also the nature of use, i.e., context of use and purposes (DeLone and McLean, 2003).
- By *"people*", we aim to observe how human work is involved in value creation and extract information about data users in organizations, their roles, business functions, and any associated skillsets and competencies, etc.
- By "*organization*", we aim to capture organizational practices, and multilevel business outcomes related to the data use, i.e., at the individual level, group level, and firm level (Burton-Jones and Gallivan, 2007; Schryen, 2013).

The dimensions of our framework provide a structured approach for information extraction and allow us to reflect on the interplay between these dimensions. These reflections will further support our conceptualization of data in organizations.

3 Research Methodology

Our literature review follows the guidelines of Webster and Watson (2002) by following structured steps of scoping, analyzing, assessing, and synthesizing earlier research. Through these steps of organizing the literature, we seek to offer a broad perspective of an emergent area (Leidner, 2018). We employed a combination of inductive and deductive approaches in our analysis at different stages. We began with an inductive literature analysis, searching for themes and patterns. As we progressed, we incorporated a deductive approach, with a high-level synthesis by pulling together evidence in the prior literature and integrating concepts across domains. The goal is to combine the findings from various sources to form a basis for developing new theories or furthering existing ones (Schryen *et al.*, 2020; Watson and Webster, 2020).

3.1 Literature search and selection

We used Web of Science as the main database, supplemented by the elibrary of AIS (AISeL) and Google Scholar for targeted searches. To cover all related discussions about data use, and data value or impact, in organizations or in the marketplace, we used search strings that contain variations of keywords: "data business value or strategic value", "data value or valuation", "data use (or analytics) and performance (or impact)", "data monetization", "data commodity", and "data marketplace". We excluded lecture notes and book chapters that were not peer-reviewed. We limited the search within categories of Information Systems and Management fields.

We considered papers available since 2000, given this is when discussions about data value started to emerge, but we observe most of the literature falls into the period post 2010. To account for recent studies, we also searched the proceedings of leading IS conferences (ICIS, ECIS, AMCIS, PACIS, HICSS) through Google Scholar and AISeL. The searches resulted in a collection of 1,108 articles, before applying further screening criteria. The selection process is presented in Figure 1.

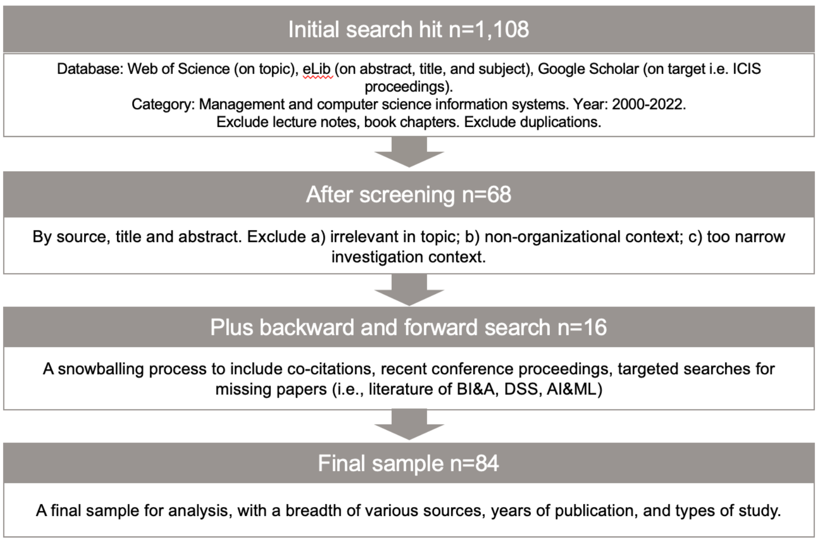
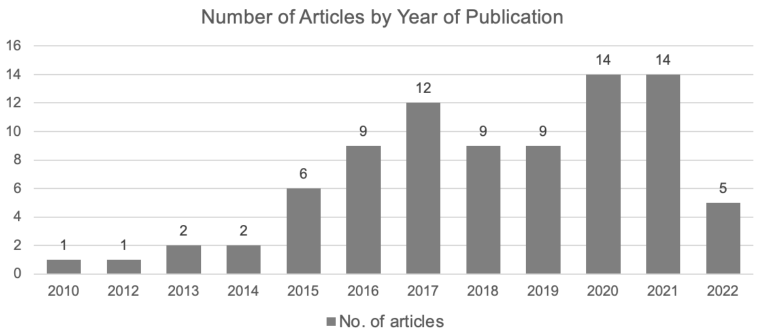


Figure 1: Literature search and selection process.

We conducted a manual screening of each article to identify its relevance to our study. Our inclusion and exclusion criteria considered several factors. To begin with, we assessed the content by title and abstract, considering its relevance to answering our research questions. While there is a vast related body of literature, our study focuses on investigating the roles and value of data, thereby limiting our search primarily to the data business value domain and the motivational aspect of data use (Surbakti et al., 2020). Specifically, we looked for articles that mentioned a data use purpose or context and possible business outcomes. We then excluded investigations of non-organizational context or overly narrow business scenarios; this helps to restrict the discussions to an organizational setting and enables mid-range generalizability of our research findings. Given that data have been discussed very broadly over the past decade, this step excluded many articles from the initial dataset, resulting in 68 articles.

Further, we conducted a backward and forward snowballing process (Webster and Watson, 2002) to include more literature via a bibliometric co-citation approach. We used seminal data value research papers as concept-centric "seeds" to identify those who cited them or those whom they cited, to identify links in concept development. We also performed targeted searches for missing papers that included more recent adoptions of business intelligence and analytics (BI&A), decision support systems (DSS), AI and machine learning initiatives, and so on. The backward and forward process yielded an additional 16 articles, resulting in a final dataset of 84 articles.

The selected articles spanned across 27 different journals and 6 peer-reviewed conference proceedings, with broad coverage of research methods (empirical vs non-empirical), sources, and years of publication (Figure 2). A detailed composition of articles by source title is enclosed in Appendix 1.



Final Sample Composition	No. of Articles
Total	**84**
By type of study	
Empirical	57
Non-empirical	27
By source	
Journal	65
Conference	19

Figure 2: Literature selection - the final sample composition.

3.2 Literature coding, mapping, and analysis

Apart from a general set of codes to assess and label the sampled articles, i.e., empirical v.s. non-empirical, research methods, keywords, concepts, and theories, we also included key dimensions as discussed in Section 2. These dimensions and units of analysis or descriptions are outlined in Table 1:

Dimension	Unit of Analysis / Description
Data Artifacts	Forms of technology or system, data artifacts, data source
Use Dimension	The purpose of use, the context of use, tasks, and processes
People Dimension	User roles, business functions, skillsets, or competencies if any
Organization Dimension	Organizational practices, business outcomes, performance measures
The Interplay	The interactions between system, people, and organizational practices

Table 1: Dimensions of literature analysis and their descriptions.

While starting with these dimensions, we kept both dimensions and units of analysis open-ended to allow subtle variations of discourse to emerge, akin to an interpretive qualitative way of organizing (Leidner, 2018). We grouped codes when we encountered little variation in a dimension and created additional subgroups when we observed a diverse coverage of the information. We not only examined the title and abstracts but also analyzed texts within the literature. These structured yet flexible steps helped us do a back-and-forth examination of the literature and balance between internal consistency and divergence of measures across the literature.

Based on the literature coding and analysis, we mapped the literature into key themes and labelled them by the purpose of use - this dimension has relatively rich information and with subtle variances, which helped us differentiate patterns. Results of the literature analysis and mapping are enclosed in Appendix 2. We further elaborate on the findings in the following sections.

4 Literature Review and Synthesis

In this section, we integrate what has been discussed in the literature and gather the key themes related to data use and their resulting value in organizations. Our primary interest lies in identifying the business purposes for which data are used and the associated outcomes. Furthermore, we are attentive to any key features of data or patterns of interaction during the process. In the following sections, we unpack each research theme through a brief recount of the discussions, as well as a general indication of the representation of these themes in the field.

4.1 Data use for business decision-making

Research indicates one of the core ways that data create value is by enhancing decision-making or enabling more informed strategic planning, and that data use is associated with improved business results, e.g., higher productivity and market value. Studies on this theme focus on the impact of data adoption in the decision-making process and its correlation with business results. Indeed, the IS body of literature on data-driven decision-making is rich and extensive (Abbasi *et al.*, 2016). In total, 23 articles report with this particular purpose of data use, which accounts for 27% of the total sample.

Data-driven decision-making is extensively studied under this theme. Data is the foundational block of information for decision-making (Barkin and Dickson, 1977; Delone and Mclean, 1992; Alavi and Leidner, 2001). Both theoretical and empirical studies reveal that economic and social value can be gained from data through business decision-making (Mithas, Ramasubbu and Sambamurthy, 2011; Chen *et al.*, 2012; Sharma, Mithas and Kankanhalli, 2014) or strategizing (Constantiou and Kallinikos, 2015; Grover *et al.*, 2018). Studies identify that data play a vital role in the process of business strategizing by informing managers and decision-makers (Pfeffer and Sutton, 2006; Grover *et al.*, 2018). Empirical evidence also shows that data-driven decision-making is correlated with better business performance (Brynjolfsson and McElheran, 2016).

The types of data artifacts to support decision-making and strategizing processes evolve over time. Constantiou and Kallinikos (2015) point out a shift from predefined data in standard strategy context to "steadily updatable" real-time data in big data ecosystems.

Under this theme, we observe the user is a key factor in the value creation process. The data value comes from informing decision-makers and therefore falls under the umbrella of evidence-based management (Pfeffer and Sutton, 2006) or structured managerial practice (Brynjolfsson and McElheran, 2016). Hence, the value of data is relative to the user; and its situated practice or purpose is decided by the user (Jones, 2019). We point this out because while we move to other types of data use, the role of human involvement (e.g., the user) seems to vary, other factors may also play roles during value creation, such as a marketplace, business processes, or even machines.

4.2 Data use for trading or selling

This theme focuses on data use for a purpose of trading or selling, commonly in an inter-organizational setting, which differentiates it from other types of use that are often inside an organization. Research related to this theme focuses on data-related business models and interactions of the two-sided market (i.e., buyers and sellers).

In total, 21% of our dataset report this particular purpose of use, representing an emerging but important direction for research. We observe a few streams of discussion related to this theme, viz*,* data liquidity, data commodity, data business models, data marketplaces, and data valuation, which signals a diverse coverage of the topic, often cross-disciplinary. We briefly explain these in the following.

Data liquidity. Yuchtman and Seashore (1967) identify that some resources are relatively "liquid" in the traditional economic sense and are readily exchangeable by an organization for resources of other kinds. More recently, Birch, Cochrane and Ward (2021) argue that data can be "assetized", and personal data can have measurable and legible value and be potentially converted into future revenue streams. Empirical evidence further supports that data can be treated as liquid assets, while "an asset is liquid if it can be converted into cash quickly and at a low cost" (Wixom, Piccoli and Rodriguez, 2021). Data liquidity is thereafter proposed and defined as “the ease of data reuse and recombination" (Wixom, Piccoli and Rodriguez, 2021; Piccoli *et al.*, 2022).

Data commodity. Aaltonen, Alaimo and Kallinikos (2021) track the transformation of data tokens into data commodities, through a case study of a telecommunications company that turned personal subscribers of their network infrastructure into a profitable advertising audience. The authors conclude that the "open and editable nature" of digital data makes them "diffusible items for exchange, repurposing, and aggregation".

Data business models. Investigations also include business models for data trading, or data-based service offerings (Alfaro *et al*., 2019; Najjar and Kettinger, 2013; Schüritz, Seebacher and Dorner, 2017; Lange, Drews and Höft, 2021; Ye *et al*., 2021) as well as data pricing strategies or policies (Chen and Huang, 2016; Mehta *et al.*, 2021).

Data marketplace. Data trading involves a *two-sided market,* buyers and sellers (Spiekermann, 2019; Parvinen *et al.*, 2020). While an information gap may exist between them (Agarwal, Dahleh and Sarkar, 2019), in some cases, a demonstration of data offerings would help seal a deal (Ray, Menon and Mookerjee, 2020).

Data valuation. When organizations are willing to trade their data assets with external buyers, data valuation becomes a core question. Empirical evidence reveals that many organizations struggle to price their data offerings as they find it difficult to define their value. Therefore, bargaining over data value becomes an intricate issue in the marketplace, especially when buyers often have diverse needs in data yet they "have no prior on the usefulness of individual datasets on sale" (Agarwal, Dahleh and Sarkar, 2019). In some cases, e.g. crowdsourcing of data goods, mathematical models may help evaluate data goods and decide on a fair price (Agarwal, Dahleh and Sarkar, 2019; Mehta *et al.*, 2021).

In general, data for business use are always contextualized and embedded in organizational practices (Grover *et al.*, 2018). Yet, relative to other types, data traded as commodities are more separable from organizations. Research finds that data in their original forms, i.e., data tokens, are transformable into data commodities by a process of decontextualizing from their organizational setting, and recontextualizing to be repurposed and recombined into new solutions (Jarvenpaa and Penninger, 2019; Aaltonen, Alaimo and Kallinikos, 2021). Studies on this theme emphasize the features of data as their ease of reuse, recombination, editability, and exchangeability (Aaltonen, Alaimo and Kallinikos, 2021; Piccoli *et al*., 2022).

4.3 Data use for innovation and learning

Digital innovation is another key theme. This theme focuses on data driven value creation through a designed business process, or a workflow, from data generation to knowledge creation to improve service or product offerings (Grover *et al*., 2018; Sadiq *et al*., 2022). Research related to this theme focuses on how to build organizational capabilities by using data for continuous business improvements.

In total, 38% of the papers in our dataset report on a purpose of data use for innovation and learning, representing a significant yet continuously evolving stream of research.

Studies indicate that data create value in digital innovations and help firms to choose the best production technique or higher quality products (Ghasemaghaei and Calic, 2020; Alaimo and Kallinikos, 2022; Hagiu and Wright, 2020). We observe a few commonly used concepts that are interwoven with this research focus, described as follows:

Data-driven organizations, or *data-driven value creation.* Research identifies that data use can cover all business processes throughout an organization which can involve multiple users from many functional areas (Sharma *et al*., 2010). Data-driven work is an enterprise-wide capability in which analytics should be woven into the fabric of an organization (Sadiq *et al*., 2022). Discussions of this stream often relate data use for business improvement processes (Duan, Cao and Edwards, 2020; Gupta *et al*., 2020; Alaimo and Kallinikos, 2022). These processes form a unique set of capabilities or competence, like the "muscles" of an organization, which sustains its competitive advantages by doing things repeatedly well.

Organizational capability. Capabilities represent "repeatable patterns of actions" to create, produce, or offer new or improved products to a market (Wade and Hulland, 2004). Research suggests that any organizational capability is the result of an organizational learning process which gradually develops a specific way of "selecting and linking" resources (Schreyögg and Kliesch ‐ Eberl, 2007). These capabilities are even more important in a "dynamic, unstable, or volatile" environment (Wade and Hulland, 2004). Hence, *dynamic capability,* often paired with the Resource-based View theory, is a commonly observed concept within this stream of discussions.

Data-enabled learning, and *data network effect.* These concepts describe a unique effect that organizations can learn from their user data to improve product offerings or services, therefore the value of their service or product is leveraged by the amount of data they own or operate on. This is typically observed with big tech companies, such as Meta (previously Facebook) and Google (Hagiu and Wright, 2020). Yet, the *data network effect* is also discussed when data are utilized in building platform AI capabilities (Gregory *et al.*, 2021).

Abundant case studies provide empirical evidence of this theme, demonstrating the value of data in digital innovations and organizational learning, such as Netflix (Gomez-Uribe and Hunt, 2015), Westpac (Anand, Sharma and Coltman, 2016), Microsoft (Wixom and Farrell, 2019), and Uber (Farronato *et al*., 2020).

Although the role of human decision-making is also visible throughout the discussions, we distinguish this theme by the interplay between data, people, and the organization. We observe the data use under this theme often requires a combination of organizational capacity across many business functions. People are just one part of this ensemble, more importantly, it is the repeatable practice that embeds data in the continuous business processes, so that organizations' competitive advantages can be sustainable.

4.4 Data use for modelling and automation

Our last identifiable theme describes the data value by their "computational power" (Orlikowski and Iacono, 2001). Today, AI technologies are rapidly changing the business landscape given contemporary organizations have opportunities to utilize a vast amount of data (Makridakis, 2017). Powerful algorithms are built and deployed to work autonomously on behalf of humans and make decisions (Newell and Marabelli, 2015). Recent research under this theme focuses on the interactions between humans and machines in battling over decision power (Galliers *et al.*, 2017; Shollo *et al.*, 2022), risk control (Marjanovic, Cecez-Kecmanovic and Vidgen, 2021), data stewardship (i.e., data quality and quantity) (Sadiq and Indulska, 2017), and legitimation of the data use (Gregory *et al.*, 2021).

Observed as a relatively recent topic, 12 representative articles (14% of the total) fall under this theme, representing an emergent yet promising direction of research. Studies identify that data in different forms of AI and ML applications create value and impact business results by reshaping business models, improving corporate offerings (Fanti, Guarascio and Moggi, 2022; Wiener, Saunders and Marabelli, 2020), or optimizing business processes (Ransbotham *et al.*, 2017).

Algorithmic Decision-Making (ADM). The vision of the field of machine learning goes beyond acting as a decision support system to human work. Instead, it advances to create artificial agents to replace human labour (Schuetz and Venkatesh, 2020). Research finds algorithms now play a vital role in processing rules, making decisions autonomously and automating business processes out of human intervention (Rinta-Kahila *et al.*, 2021; Sadiq *et al.*, 2022).

Algorithmic pollution. In some cases, automated decision-making algorithms out-rule human decisions (Marjanovic, Cecez-Kecmanovic and Vidgen, 2021; Galliers *et al.*, 2017; Enholm *et al.*, 2021; Shollo *et al.*, 2022). However, unintended consequences of such use, for example, discrimination and social inequality, may destruct society (Rinta-Kahila *et al.*, 2021) . Research also takes an active role studying these negative effects, denoted as "algorithmic pollution" (Marjanovic, Cecez-Kecmanovic and Vidgen, 2021), and exploring how to contain or mitigate such negative effects during algorithms-driven decision-making processes (Rinta-Kahila *et al.*, 2021).

Lastly, we observe that human involvement is designed to become relatively low under this theme. In some cases, the machine can even act out of human intervention. Yet, algorithms are only able to make sensible decisions or prescribe a set of programmed actions if they are embedded with precisely contextualized organizational processes.

5 Our Proposed Conceptualizations of Data in Organizations

Next, to better understand the roles of data in organizations, we take a further step towards synthesizing arguments that describe the features and attributes of data in an organizational context. By pulling together evidence in the literature, we propose to conceptualize data into four categories, each representing a distinct set of data features associated with their use.

Our conceptualizations of data are largely based on the theoretical discussions of data, digital artifacts, and IT artifacts argued in previous conceptual papers. Orlikowski and Iacono (2001) introduce their five views to theorize IT artifacts. At intervals, assessments of the theory in the IS field have confirmed consistent results (Matook and Brown, 2017). In recent years, in responding to digital developments, several studies have also provided insights by theorizing digital artifacts (Kallinikos, Aaltonen and Marton, 2013; Faulkner and Runde, 2019) and data objects (Aaltonen, Alaimo and Kallinikos, 2021; Alaimo and Kallinikos, 2022). Based on ontological assumptions (Rosemann and Green, 2002), we observe that some features of data may be inherent from a broader category such as IT artifacts and digital artifacts, while some may be emergent from their unique usage in contemporary organizations. We consider both in our synthesis.

We refer to data in an organizational context as one type of IT artifacts that are defined as a bundle of material and cultural properties packaged in a recognizable form such as hardware and/or software (Orlikowski and Iacono, 2001). They are always embedded in a context (Benbasat and Zmud, 2003) and are not considered "natural, neutral, universal, or given" (Orlikowski and Iacono, 2001).

We propose that data exhibit varying characteristics and features when used in different contexts, and these features can be categorized into several clusters. Our labels signal primary conceptualizations of data for each category, viz, data as a tool, as a commodity, as a capability, and as algorithmic intelligence.

Data as a tool. In the context of supporting human decision making, data act as a tool that is designed to serve a specific purpose. This means that data should be expected to perform as intended by their users or designers. The tool view also acknowledges that the user and the organization can adapt the use of data according to their specific needs and context (Orlikowski and Iacono, 2001; Parvinen *et al*., 2020). Data value is therefore relative to the user and the way in which data are used (Jones, 2019). When data are viewed as a tool, they can be considered separate from the organizational setting, they are "definable", "unchanging", and "independent" (Orlikowski and Iacono, 2001).

Data as a commodity. When data are traded or sold as goods, they are treated as a commodity. Recent research suggests that data can also be viewed as liquid assets as they can be easily converted into revenue at low cost, and some types of data may have a higher level of liquidity than others (Piccoli *et al*., 2022). Data are identified to be made up of distinct "atomic components" or "sign tokens" that can be easily repurposed, recombined, and restructured to create new solutions (Kallinikos, Aaltonen and Marton, 2013; Alfaro *et al*., 2019; Aaltonen, Alaimo and Kallinikos, 2021). As such, they are editable, interactive, reprogrammable, distributable, and exchangeable (Aaltonen, Alaimo and Kallinikos, 2021). Furthermore, as a type of digital artifacts, data can be decoupled from their hardware or software infrastructure due to their separability nature, as noted by Faulkner and Runde (2019).

Data as a capability. When data are used for organizational learning and innovation, a business process or workflow is involved, consisting of ordered steps from data generation to knowledge creation (Grover *et al*., 2018). This process helps sustain an organization's competitiveness in products or services (Wade and Hulland, 2004; Grover *et al*., 2018). We refer to this type of data use as a capability, which represents repeatable patterns of actions that leverage data assets for continuous improvements in operations, and for optimizations of product or service (Wade and Hulland, 2004). Data in this situation are enmeshed in the complex and dynamic social context of the organization (Grover *et al*., 2018), influenced by a combination of factors such as data resources, competencies, and practices that work together to drive business results (Aral and Weill, 2007).

Data as algorithmic intelligence. When data are used for algorithmic modelling and automation, it correlates to the computational ability of IT artifacts (Orlikowski and Iacono, 2001). Beyond that, data have the potential to demonstrate algorithmic intelligence, and they are constantly evolving and replicating human behaviours in machines. The latest example is ChatGPT that utilizes deep learning algorithms to generate human-like responses to natural language inputs (Radford *et al.*, 2019). This is achieved through algorithmic computation, which is capable of making decisions and automating business processes (Davenport *et al.,* 2018). The modular architecture of data networks makes it even more adaptable and integrable than before, which further enhances their functionality and allows for reuse and recombination in various contexts (Gregory *et al*., 2021; Raisch and Krakowski, 2021; Piccoli *et al*., 2022). These features have transformed data into a key resource for organizations, enabling them to streamline operations and achieve new levels of efficiency and effectiveness.

The diverse and dynamic use of data in contemporary organizations has resulted in some emergent roles, which contrast with their traditional uses. Based on the above, we have observed these emerging roles and their impact on organizations. Two categories in particular, data as a commodity, and data as algorithmic intelligence, have developed rather unique features and capabilities from interacting with people and the organization. These emergent roles of data have become less reliant on human orchestration in the value creation process and can also be more separable from the organizational setting. As a result of these unique features, data seem to have a greater potential for reuse and repurposing between organizations than traditional IT artifacts. OpenAI's latest release of GPT-4, being a good example, demonstrates the incredible potential of data within and across organizations. Their big language model is highly adaptable and integrable that can support numerous applications simultaneously, while their API services are being priced and traded directly between organizations and creating new revenue streams (OpenAI, 2023). Yet, as these observations are preliminary, we suggest that future research should offer more justifications.

6 Discussion and Conclusion

For over a decade, research has explored data use and its impact on organizations. Despite rich empirical evidence, data as an important organizational asset still lacks conceptual clarity that adequately reflects data's complex nature in the contemporary business context. This research contributes to the field by providing a first step towards synthesizing diverse perspectives in the literature and emphasizing the need to reconsider the roles of data in organizations. Our study illustrates that data serve multiple purposes in organizations, and their value is determined by the roles they play. By synthesizing data features and attributes associated with their use, we then offer an initial conceptualization of these roles into four categories. Through this study, we therefore demonstrate that data can provide value through a wide spectrum of conventional and novel uses in organizations.

Defining the multiple roles of data in organizations and highlighting their distinction in nature is important for the field of Information Systems. First, understanding the multiple "hats" data wear in organizations highlights that value of data should not be measured or generalized in a one size fits all manner, rather it should be contextualized based on specific use purposes. This is because the value creation process and key enablers can vary depending on the context and intended use of the data. Second, as we have attempted to establish links between the use purposes and associated features of data, it is crucial to recognize that data possess unique characteristics based on the roles they play. Therefore, they should be managed differently in various use occasions to best align with their respective features. Doing so will facilitate determination of the most effective methods for utilizing and managing data in contemporary organizations. Last, by understanding similarities and differences between data and traditional IT artifacts, researchers can reassess IT governance and the compatibility of various IT components, leading to improved integration of data into IT systems and thus supporting organizations to attain their business objectives.

While this research is preliminary, we expect organizations will benefit from our study in multiple ways. Specifically, as we clarify the unique features of data, organizations can optimize their data governance, management, and utilization strategies. This can lead to improved identification of business growth opportunities and risk management practices. In addition, as we identify the diverse sources of data value, this will help organizations to effectively leverage their data assets for multiple benefits, such as driving innovation, enhancing decision-making, trading or selling, and automating business processes.

We acknowledge that there are limitations to our research. First, while our review covers a broad literature, we recognize that our attempt to provide an overview of prior discussions may have compromised the level of detail we wish to present. Furthermore, our study takes an exploratory approach with a focus on the "what" aspect of the topic. We have not provided a comprehensive analysis of the "how" and "why" aspects that would be necessary to fully define the versatile roles of data. Future studies should delve deeper into these aspects.

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Appendix

Appendix 1: Literature selection - number of publications by source title.

	SOURCE TITLE	NO. OF ARTICLES
PEER-REVIEWED JOURNALS (64 ARTICLES)	INFORMATION & MANAGEMENT	8
	JOURNAL OF MANAGEMENT INFORMATION SYSTEMS	6
	MIS QUARTERLY EXECUTIVE	6
	DECISION SUPPORT SYSTEMS	4
	INFORMATION SYSTEMS FRONTIERS	4
	JOURNAL OF STRATEGIC INFORMATION SYSTEMS	4
	INFORMATION SYSTEMS RESEARCH	3
	JOURNAL OF BUSINESS RESEARCH	3
	JOURNAL OF ENTERPRISE INFORMATION MANAGEMENT	3
	JOURNAL OF INFORMATION TECHNOLOGY	3
	ACADEMY OF MANAGEMENT REVIEW	2
	EUROPEAN JOURNAL OF INFORMATION SYSTEMS	2
	INFORMATION SYSTEMS MANAGEMENT	2
	ACM TRANSACTIONS ON MANAGEMENT INFORMATION SYSTEMS	1
	AMERICAN ECONOMIC REVIEW	1
	BIG DATA & SOCIETY	1
	BIG DATA AND COGNITIVE COMPUTING	1
	BRITISH JOURNAL OF MANAGEMENT	1
	COMMUNICATIONS OF THE ASSOCIATION FOR INFORMATION SYSTEMS	1
	EUROPEAN JOURNAL OF OPERATIONAL RESEARCH	1
	INDUSTRIAL MARKETING MANAGEMENT	1
	INTERECONOMICS	1
	JOURNAL OF COMPUTER INFORMATION SYSTEMS	1
	JOURNAL OF INDUSTRIAL AND BUSINESS ECONOMICS	1
	JOURNAL OF KNOWLEDGE MANAGEMENT	1
	MANAGEMENT DECISION	1
	INFORMATION SYSTEMS JOURNAL	1
	NATIONAL BUREAU OF ECONOMIC RESEARCH	1
CONFERENCE PROCEEDINGS (20 ARTICLES)	ECIS	5
	HICSS	4
	ACIS	3
	BUSINESS INFORMATION SYSTEMS WORKSHOPS	3
	ICIS	3
	ACM EC	1

Appendix 2: Literature analysis: a total sample of literature selected and their identified themes after mapping.

LITERATURE CITED AS	STUDY TYPE	RESEARCH THEME			
		DECISION MAKING	TRADING OR SELLING	INNOVATION AND LEARNING	MODELLING AND AUTOMATION
Trkman, P. et al. (2010)	Empirical			X	
Chen, H. et al. (2012)	Non-empirical	X		X	
Blohm, I., Leimeister, JM. and Krcmar, H. (2013)	Empirical	X			
Najjar, MS Kettinger, WJ. (2013)	Empirical		X		
Bekmamedova, N and Shanks, G. (2014)	Empirical	X			
Sharma, R., Mithas, S. and Kankanhalli, A. (2014)	Non-empirical	X			
Someh, I.A. and Shanks, G.G. (2015)	Empirical	X			
Chen, DQ., Preston, DS. and Swink, M. (2015)	Empirical			X	
Constantiou, Ioanna D and Kallinikos, Jannis (2015)	Non-empirical	X			
Newell, Sue and Marabelli, Marco (2015)	Non-empirical				X
Gomez-Uribe, C.A. and Hunt, N. (2015)	Empirical			X	
Caya, O. and Bourdon, A. (2016)	Non-empirical	X			
Zolnowski, A., Christiansen, T., & Gudat, J. (2016)	Empirical			X	
Smith, G., Ofe, H.A. and Sandberg, J. (2016)	Empirical		X		
Anand, A. Sharma, R. and Coltman, T. (2016)	Empirical			X	
Chen, Y.J. and Huang, K.W. (2016)	Empirical		X		
Brynjolfsson, Erik and McElheran, Kristina (2016)	Empirical	X			
Gupta, Manjul and George, Joey F. (2016)	Empirical			X	
de Vries, A. Chituc, CM. and Pommee, F. (2016)	Empirical	X			
Shollo, A. and Galliers, R.D. (2016)	Empirical	X		X	
Côrte-Real, N., Oliveira, T., and Ruivo, P. (2017)	Empirical			X	
Wang, Y. and Byrd, T.A. (2017)	Empirical	X			
Fink, L. Yogev, N. and Even, A. (2017)	Empirical			X	
Schüritz, R. Seebacher, S. and Dorner, R. (2017)	Empirical		X		
Galliers, R. D.et al. (2017)	Non-empirical				X
Marijn Janssen, Haiko van der Voort and Agung Wahyudi (2017)	Empirical	X			
Trieu, VH. (2017)	Non-empirical	X			
Breidbach, Christoph F. (2017)	Empirical			X	
Chen, H.M., Schutz, R., Kazman, R. and Matthes, F. (2017)	Empirical			X	
Pappas, IO.et al. (2017)	Non-empirical	X			
Sammon, D. and Nagle, T. (2017)	Non-empirical		X		
Kitchens, B., Dobolyi, D;., Li, JJ. and Abbasi, A. (2018)	Non-empirical	X			
Erik Brynjolfsson, Daniel Rock and Chad Syverson (2018)	Empirical				X
Krishnamoorthi, S. and Mathew, SK. (2018)	Empirical			X	
Grover, V., Chiang, RHL., Liang, TP. And Zhang, DS. (2018)	Non-empirical	X		X	
Song, PJ., Zheng, CD., Zhang, C. and Yu, XF. (2018)	Empirical	X			
Kühne, B. and Böhmann, T. (2018)	Non-empirical		X		
Muller, O., Fay, M. and vom Brocke, J. (2018)	Empirical			X	
Popovic, A,. Hackney, R,. Tassabehji, R. and Castelli, M. (2018)	Empirical			X	
Sun, S., Casey G. Cegielski, Lin Jia and Dianne J. Hall (2018)	Non-empirical			X	
Agarwal, A., Dahleh, M. and Sarkar, T. (2019)	Non-empirical		X		
Alfaro, E., et al. (2019)	Empirical		X		
Mikalef, P; Boura, M; Lekakos, G; Krogstie, J. (2019)	Empirical			X	
Ferraris, A., Mazzoleni, A., Devalle, A. and Couturier, J. (2019)	Empirical			X	
van de Wetering, R., Mikalef, P. and Krogstie, J. (2019)	Empirical			X	
Spiekermann, M. (2019)	Empirical		X		
Kühne, B. and Böhmann, T. (2019)	Empirical		X		
Ghasemaghaei, M. (2019)	Empirical	X			
Shamim, S. et al. (2019)	Empirical	X			
Gupta, S. et al. (2020)	Empirical			X	
Parvinen, P. et al (2020)	Empirical		X		

(continued)

LITERATURE CITED AS	STUDY TYPE	RESEARCH THEME			
		DECISION MAKING	TRADING OR SELLING	INNOVATION AND LEARNING	MODELLING AND AUTOMATION
Faroukhi, A.Z., et al. (2020)	Non-empirical			X	
Ghasemaghaei, M. and Calic, G. (2020)	Empirical			X	
Ray, J., Menon, S; Mookerjee, V. (2020)	Non-empirical		X		
Olszak, CM. and Zurada, J. (2020)	Empirical			X	
Wiener, M., Saunders, C. and Marabelli, M. (2020)	Non-empirical		X		
Dong, JQ. and Yang, CH. (2020)	Empirical			X	
Farouk, Firdous Mohd and Siew, Eugene (2020)	Empirical			X	
Surbakti, F. et al. (2020)	Non-empirical	X			
Mantymaki, M, Hyrynsalmi, S. and Koskenvoima, A. (2020)	Empirical	X			
May, A., et al. (2020)	Empirical			X	
Duan, YQ., Cao, GM. and Edwards, JS. (2021)	Empirical			X	
Rinta-Kahila, T. et al. (2021)	Empirical				X
Marjanovic, O., Cecez-Kecmanovic, D. and Vidgen, R. (2021)	Empirical				X
Enholm, I.M., et al. (2021)	Non-empirical				X
Mikalef, P. and Gupta, M. (2021)	Empirical				X
Saleem, H., et al. (2021)	Empirical			X	
Birch, K., Cochrane, D.T. and Ward, C. (2021)	Empirical		X		
Delgosha, M.S., Hajiheydari, N. and Fahimi, S.M. (2021)	Non-empirical	X			
Mehta, S., Dawande, M., Janakiraman, G. and Mookerjee, V. (2021)	Non-empirical		X		
Ye, H., Yang, X., Wang, X. and Stratopoulos, T.C. (2021)	Empirical		X		
Lange, H. E., Drews, P., and Höft, M. (2021)	Empirical		X		
Aaltonen, A., Alaimo, C. and Kallinikos, J. (2021)	Empirical		X		
Gregory, R.W., Henfridsson, O., Kaganer, E. and Kyriakou, H. (2021)	Non-empirical			X	X
Gregory, R. W., Henfridsson, O., Kaganer, E., and Kyriakou, H. (2022)	Non-empirical			X	X
Roeder, J., Palmer, M. and Muntermann, J. (2022)	Empirical	X			
Jamwal, A.et al. (2022)	Non-empirical				X
Shollo, A., Hopf, K., Thiess, T. and Müller, O. (2022)	Empirical			X	X
Fanti, L., Guarascio, D. and Moggi, M. (2022)	Empirical				X

Notes: 1) Some articles cover multiple themes, for example, Chen *et al*., 2012; Grover *et al*., 2018; Shollo *et al*., 2022. 2) A few articles in our final sample are not listed here - they are reviewed but not grouped into any of the themes. That includes several literature reviews such as Günther, *et al*., 2017; Baecker, *et al*., 2021; Klee, *et al*. 2021, plus a couple of articles that do not specify how data are used, such as Ghasemaghaei, *et al*. 2015; Huang, *et al*. 2020.

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