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Towards a reference ontology for a data valuation business capability

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ABSTRACT
Despite its recognition as primary asset, enterprises struggle to determine data value due to fragmented and impractical approaches. This paper develops a reference ontology for Data Valuation Business Capabilities (DVBC) leveraging the systematic approach for building ontologies, ArchiMate and integrating scientific insights with ex-ante expert interview validation. Comprising twelve groupings and 66 components, anchored in established ontologies and assessed against (non)-functional requirements, the ontology shapes the fragmented data valuation landscape into a structuring frame for enterprises. While advancing value modelling in information systems research, the ontology faces limitations like detailed process modelling deficiency, ex-post validation potential, and modelling language boundaries.

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Introduction

'The demand for data valuation is fast growing' (Fleckenstein, Obaidi, and Tryfona 2023). However, data and its associated value are subject to interpretation from various perspectives, necessitating a precise definition of data and its corresponding value.

Scholars have made numerous attempts to delineate the concept of data and related terminologies, such as information and knowledge. For instance, researchers have approached these terms from a cascading perspective, starting with raw data as a carrier and culminating in knowledge via contextualisation of data to information (Benjamin Martz and Shepherd 2003; Thomas H Davenport 2001; W. Zhang 1994) or vice versa, employing a materialisation approach from knowledge to data (Kettinger and Li 2010; Tuomi 1999). Alternative theories, like the knowledge-based theory of information proposed by Kettinger and Li (2010), suggest that information emerges through the interplay of data and knowledge. For example, data entails a representation of states, such as the output from a temperature sensor recording the temperature curve of a production machine in degrees Celsius. Knowledge, representing the associations between concepts emerging from these states, encompasses logic, e.g. forecasting future temperature conditions based on the production machine's temperature curve. The interplay between data and knowledge shapes information, representing the readiness for action. For

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instance, transmitting information to a production specialist to adjust the production machine's speed in response to the contextual interpretation of temperature trend data and future predictions, signalling potential overheating.

While both scholars and businesses hold diverse interpretations of data, information, and knowledge, the demand for modelling their value remains high (Sales et al. 2018). At this stage, data valuation covers an overarching approach that addresses the value of data, information, or knowledge customised to meet the needs of scholars or professionals. To facilitate the understanding of the evolving reference ontology, the term data encompasses data, information, and knowledge, thereby allowing for a simplified definition of *data in context*. This data in context contributes to the overall monetary and non-monetary business value for enterprises (Elia et al. 2020), encompassing economic benefits (Attard and Brennan 2018), functional enhancements such as improved decision-making, and the perception of the enterprise within its ecosystem, among other factors tailored to an enterprise (Meierhofer et al. 2022).

One core need of academia and real-world enterprises is formalising the above-mentioned data valuation (Hafner and Mira da Silva 2023; Kaufmann 2019; Noshad et al. 2021). A reason for this is the struggle of enterprises to determine the value of their data, while at the same time, 'data's worth is dramatically increasing' (Mavrogiorgou et al. 2023) and data is increasingly recognised as a strategic asset (Brennan et al. 2019; Faroukhi et al. 2020; Fleckenstein, Obaidi, and Tryfona 2023; Hafner et al. 2022; Thieullent et al. 2020). Considering the growing importance assigned by enterprises to data, it becomes imperative to explore data valuation.

The existing literature presents distinct approaches for determining data value that vary in perspective, type, scope, and content (Fleckenstein, Obaidi, and Tryfona 2023; Hafner and Mira da Silva 2024). Certain scholars examine data valuation through a market-oriented game theory lens, aiming to distribute the value of data among various participants in a data market (Jia, Dao, et al. 2019; Liang et al. 2018).

While market-based and economic-based approaches focus on the costs and revenues or the economic and public benefits of data, other approaches, like the dimensional data valuation approach, directly compare different datasets (Fleckenstein, Obaidi, and Tryfona 2023). Dimensional approaches consider both intrinsic data value drivers, such as data quality (Fleckenstein, Obaidi, and Tryfona 2023; Fricker and Maksimov 2017) or data privacy (Jung et al. 2019; Shen et al. 2022), and contextual data value drivers, such as data usage (Brennan et al. 2019; Fleckenstein, Obaidi, and Tryfona 2023), the perceived data exclusivity (Heckman et al. 2015; Spiekermann and Korunovska 2017) or risk affinity of involved stakeholders (Shen et al. 2016; Yang and Xing 2019).

Whereas dimensional approaches strongly emphasise the interpersonal collaboration of stakeholders to determine the value of data, e.g. via surveys (Fleckenstein, Obaidi, and Tryfona 2023), other scholars approach data valuation instead from a technological angle, e.g. utilising trustworthy and fair machine learning algorithms (Jia, Dao, et al. 2019; Mavrogiorgou et al. 2023) and blockchain-based data market architectures (Mavrogiorgou et al. 2023). The latter examines data value from an architectural perspective, wherein architectural layers, such as security, trading, or data asset management, are described to offer components for determining data value and facilitating the exchange of data assets and their associated data value among market participants (Mavrogiorgou et al. 2023).

Examining these diverse perspectives, scholars and professionals frequently encounter encapsulated and fragmented concepts in data valuation, presenting challenges for enterprises aiming to adopt these approaches. Wu, Shu, and Low (2022) underscore this challenge to a greater extent, highlighting that 'developing trustworthy data valuation methods that are explainable, fair, and robust is [. . .] extensively required to measure the value of data and also decide how to use them in real-world applications'. This lack of robust data valuation approaches can lead to, e.g. inconsistent valuations followed by ineffective decision-making, which results in competitive disadvantages (Schneider et al. 2022).

To attain long-term competitive advantages by enhancing responsiveness to changes and different perspectives on data valuation, scholars have stressed the need to adopt capability-centric thinking (Aldea et al. 2015a; Azevedo et al. 2013). Further, Liang et al. (2018) specifically pointed towards the urge that future research should place 'more efforts [. . .] for understanding different types of data and the design of proper models to realise the exact values for different kinds of data users'. Thus, developing a business capability dedicated to data valuation is a viable strategy for harmonising diverse approaches for data valuation (Hafner and Mira da Silva 2023).

Nevertheless, establishing a data valuation business capability (DVBC) entails a significant complexity, which varies depending on the patterns deemed relevant for data valuation. Brennan, Attard, and Helfert (2018) specifically underlined that future research is required on 'data value monitoring infrastructure; formal models describing metrics, dimensions and how they relate (ontologies or data models)'. Examining these complexity management challenges and suggested avenues for future research, this paper delves into data value ontology engineering (Falbo 2014; Guarino, Oberle, and Staab 2009), particularly for a DVBC.

Ontologies were initially conceived in philosophy to classify entities based on their nature and structure, irrespective of their actual existence. In information systems research, ontologies are viewed as artefacts that conceptually structure an area of interest or so-called domain, in this case, data valuation. Therefore, ontologies define concepts, relationships, and reasoning rules, often relying on taxonomies as their foundational structure. Ontologies enable the formal representation of a domain by using structuring meta-models and modelling languages to facilitate knowledge creation through abstraction and conceptualisation (Guarino, Oberle, and Staab 2009; Guizzardi 2006; Noy 2001). Thus, ontologies are vital in providing a standard and shared understanding of the created knowledge (Ali et al. 2019; da Silva Serapião Leal, Guédria, and Panetto 2020). Ontologies, in general, and reference ontologies, in particular, offer several benefits, such as providing accurate and concise definitions of models based on real-world significance, identifying issues related to the interpretation, meaning, or application of concepts (Falbo 2014) and the potential of evolving over time based on emerging requirements from academia and enterprises (Pfaff and Krcmar 2018). Moreover, ontologies foster knowledge structuring among diverse stakeholders, enhancing the potential for reusing domain-specific knowledge across research areas (da Silva Serapião Leal, Guédria, and Panetto 2020; Noy 2001), such as information systems research (Pfaff and Krcmar 2018), engineering (Q. Wang et al. 2017), business (da Silva Serapião Leal, Guédria, and Panetto 2020), and healthcare (Hadzic, Chen, and Dillon 2008). This underscores their versatility and applicability across diverse fields of study.

Considering the fragmented landscape of data valuation approaches in academia and the difficulties enterprises encounter in determining data value, this study aims to harness the advantages of ontology engineering. It seeks to develop a DVBC reference ontology that bridges the divide between theoretical approaches and practical applications. Consequently, the purpose of this study is to (a) represent data value determination as a business capability in an enterprise architecture context, (b) understand ontological components and their relationships of a DVBC, and (c) embed the DVBC reference ontology into a scientific state of the art using existing ontological reference patterns. Therefore, two research questions can be identified.

- RQ1: What ontological components are associated with data valuation?
- RQ2: How are the ontological components of data valuation related to each other in the context of business capabilities?

This paper is structured in six sections to answer the research questions. While the following section focuses on the research background, the subsequent section addresses the applied methodologies. Section *reference ontology design and development* explains the DVBC reference ontology before the study finishes with a discussion and conclusion.

Research background

The present section contextualises and defines core terminologies for the DVBC reference ontology in line with the research background and the study objectives, focusing on the definitions of data valuation and business capabilities.

Data valuation

Data valuation refers to a series of logical steps used to determine the potential and/or actual value of data, either qualitatively or quantitatively (Ghorbani, Kim, and Zou 2020; Stein et al. 2021). With regard to this study and considering the various definitions from academia, data valuation is defined as a process cluster consisting of seven components: data preparation and contextualisation, data value assessment (Brennan, Attard, and Helfert 2018; Hafner, Proper, and Mira da Silva 2024; Stein et al. 2021), allocation (Brennan, Attard, and Helfert 2018; Jia, Li, et al. 2019), prediction (Brennan, Attard, and Helfert 2018; Holst et al. 2020), realisation (Hafner, Proper, and Mira da Silva 2024), monitoring (Brennan, Attard, and Helfert 2018; Debattista, Attard, and Brennan 2018), and accompanying change management (Hafner, Proper, and Mira da Silva 2024).

Business capability

Like the term data valuation, the definition of a business capability lacks consistency in academic literature. According to the condensed findings of a literature analysis on business capabilities conducted by (Offerman, Stettina, and Plaat 2017), a business capability can be defined as an enterprise's ability to accomplish a particular organisational objective. Alternatively, the definition of a business capability according to *The Open Group Architecture Framework* (TOGAF) details the rather generic definition of Offerman, Stettina, and Plaat (2017) by the business capability components information, processes, roles, and resources (Gonzalez et al. 2018).

With regard to this study, the organisational objective, according to (Offerman, Stettina, and Plaat 2017), is defined as the qualitative and/or quantitative determination of data value, which is achieved through the implementation of a DVBC. The DVBC comprises components of a business capability following TOGAF (Gonzalez et al. 2018), detailed by subcomponents that are represented as logical groupings in the DVBC reference ontology (see Figure 2).

Research methodology

This section elucidates the applied methodology and modelling language employed in developing the DVBC reference ontology, intended as an artefact within the design science paradigm (Vom Brocke, Hevner, and Maedche 2020). For the design and development of the artefact, the systematic approach for building ontologies (SABiO) following (Falbo 2014), along with the modelling framework ArchiMate (The Open Group 2019), is selected (Figure 1). Subsequently, the relevance of ontologically significant components is validated through semi-structured expert interviews. The following sections describe both SABiO and ArchiMate, including the rationale for their employment in this study.

Systematic approach for building ontologies (SABiO)

SABiO is a systematic approach to ontology engineering developed by Falbo (2014), which encompasses the development of both reference and operational ontologies. Reference ontologies can be expressed through conceptual models (Falbo 2014; Guarino, Oberle, and Staab 2009), while operational ontologies are machine-readable implementations of ontologies. Within SABiO, there are five phases in total, with two phases labelled purpose identification and requirements elicitation and ontology capture and formalisation being particularly significant for crafting a reference ontology, in this context, the DVBC reference ontology (Falbo 2014). SABiO has demonstrated its efficacy in solving complex issues in the information systems domain (Gomes, Santoro, and Silva

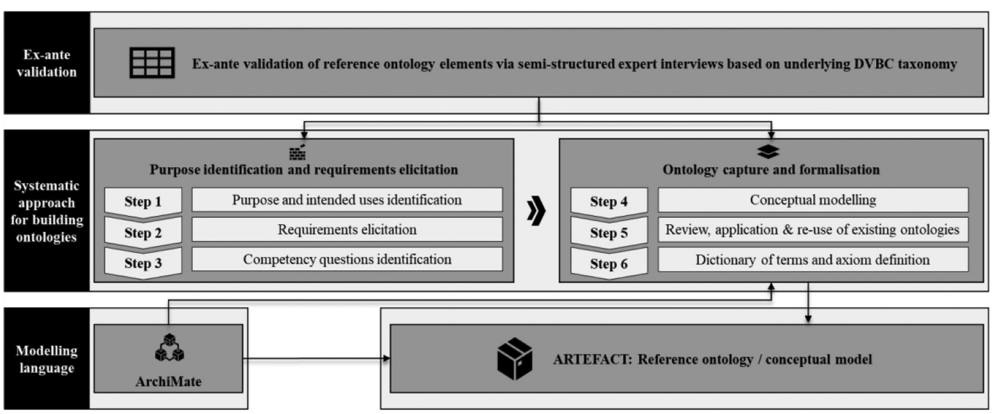

Figure 1. SABiO (Falbo 2014) applied to the DVBC reference ontology.

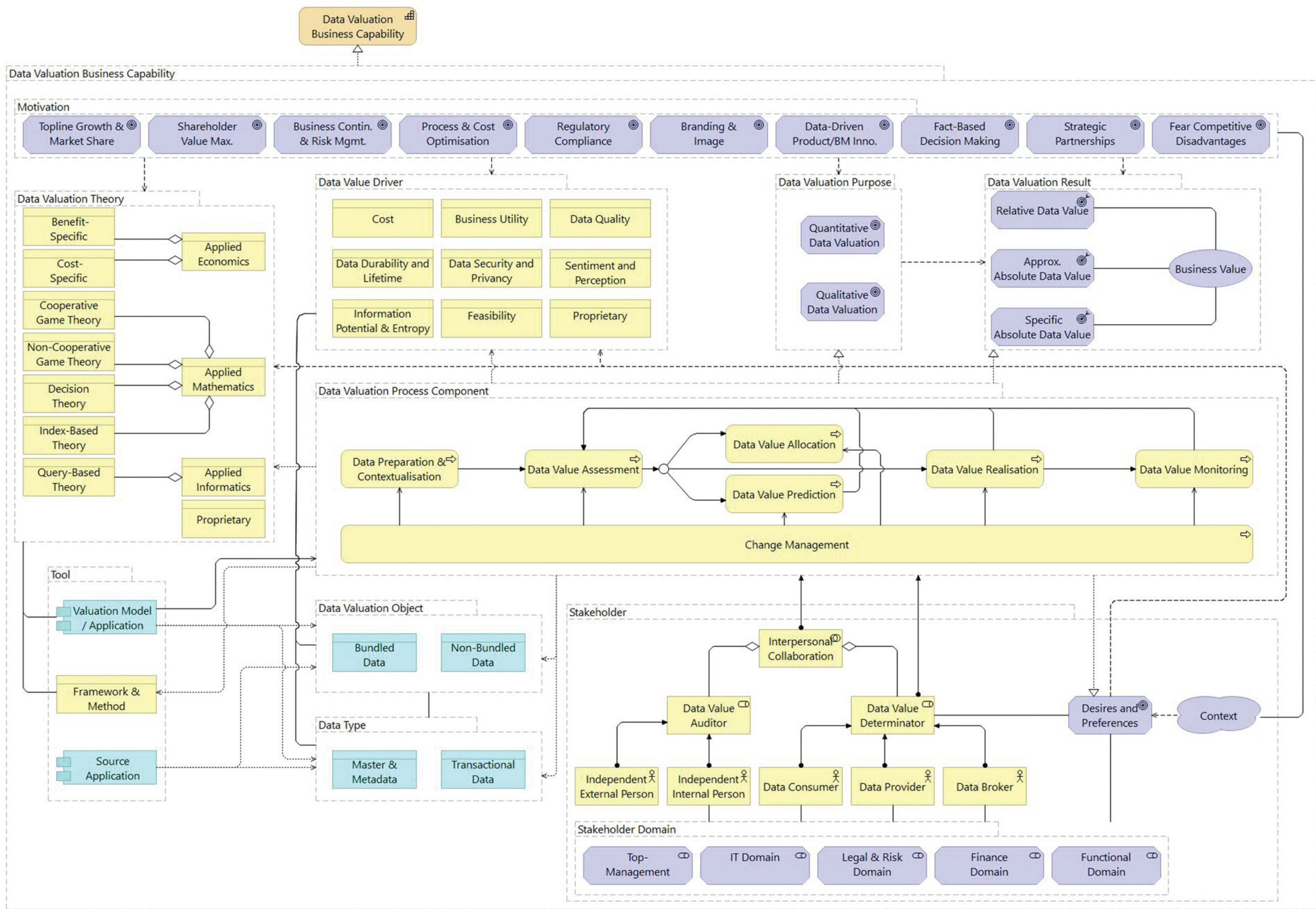

Figure 2. Data valuation business capability reference ontology.

2020; Falbo 2014). By applying SABiO, the DVBC reference ontology creation can be accomplished with adherence to quality standards such as verifiability, completeness, and reusability (Falbo 2014).

ArchiMate

The DVBC reference ontology artefact developed via SABiO is modelled using ArchiMate (The Open Group 2019), a modelling language often applied hand in hand with the TOGAF standard (Sales et al. 2019). ArchiMate describes the structure, behaviour, and relationships of an enterprise's systems, processes, and stakeholders on the architectural layers of business, application, and technology. Further, ArchiMate provides various extensions that emerged over time, such as motivation, strategy, as well as implementation and migration (The Open Group 2019). Given that ArchiMate is a language that is capable of modelling value in a broad sense (Sales et al. 2019), it is conjectured that it is also applicable to model data value and related concepts.

The graphical notations of ArchiMate make it plain for stakeholders to understand the modelled concepts and communicate the value of data to business professionals, such as CIOs, CDOs, enterprise architects and data strategy professionals. Provided that TOGAF and ArchiMate have been widely adopted in both industry (Cameron and McMillan 2013) and academia (Al-Turkistani, Aldobaian, and Latif 2021; Aldea et al. 2015b; Bui 2017) and the intended readership of this paper is accustomed to interpreting and comprehending ArchiMate models, TOGAF and ArchiMate are employed within this study. The application of TOGAF and ArchiMate is strengthened as the concept of value has especially received increased attention in recent efforts regarding utilising and extending ArchiMate (Aldea et al. 2015b). Initially, ArchiMate linked value to products and services only, but this view has since been expanded. It is now understood that value can be attributed to various other concepts in ArchiMate (Iacob, Quartel, and Jonkers 2012), including business capabilities modelling.

Reference ontology design and development

This section focuses on creating a reference ontology for a DVBC in ArchiMate, emphasising phases 1 and 2 based on SABiO (Falbo 2014).

Phase 1 – Purpose identification and requirements elicitation

During Phase 1, the strategic direction and requirements for the DVBC reference ontology are formulated and documented as competency questions. Although (Falbo 2014) proposes ontology modularisation in Phase 1, it is not adopted since the objective is to model the overall context of a DVBC. Nonetheless, the modularisation approach of the DVBC reference ontology can be considered for future research.

Purpose and intended uses identification

Articulating the purpose of the DVBC reference ontology is crucial, as it provides a sense of direction, facilitates the derivation of functional and non-functional requirements, and guides the model's ongoing development (Falbo 2014).

Table 1. Requirements for a DVBC reference ontology according to Falbo (2014).

Type	ID	Requirements/Competency questions
FR	CQ1	What is the motivation for enterprises to implement a DVBC?
FR	CQ2	What is the purpose of a DVBC?
FR	CQ3	What data objects are valued in a DVBC?
	CQ4	What types of data are valued in a DVBC?
FR	CQ5	What drivers affect the value of data?
FR	CQ6	What theories serve as a foundation for determining data value?
FR	CQ7	How can tools be applied to support data valuation?
	CQ8	Which stakeholder domains within an enterprise are involved in a DVBC?
FR	CQ9	Who are the stakeholders involved in a DVBC?
FR	CQ10	Which functionalities/components does a DVBC imply?
FR	CQ11	Which results can emerge from a DVBC?
NFR	NFR1	The DVBC reference ontology is usable and extendable for professionals and scholars in the enterprise architecture domain.
NFR	NFR2	The DVBC reference ontology aligns with scientifically sound and published concepts regarding data valuation capabilities.
NFR	NFR3	The DVBC reference ontology is grounded on scientifically sound reference ontologies to ensure interoperability standards with adjacent concepts.

This study's introduction examined research questions encompassing the paper's overall purpose. However, focusing specifically on the DVBC reference ontology, its purpose is to model correlation and dependencies of data valuation concepts in the context of business capabilities. By defining the ontological components and relationships related to data value determination, this DVBC reference ontology empowers enterprises to understand and represent data value determination as a business capability within their enterprise architecture.

Requirements elicitation and competency questions identification

Functional (FR) as well as non-functional requirements (NFR) supporting the DVBC reference ontology purpose are formulated and documented in a requirement catalogue, following the requirements/competency questions as shown in Table 1. While non-functional requirements are declaratively articulated, functional requirements, which are content-specific, are formulated as competency questions (CQ), according to SABiO (Falbo 2014). While the functional requirements, according to SABiO, cover the substantive components of the DVBC reference ontology, the non-functional requirements address quality, extensibility, and reusability (Falbo 2014).

The DVBC taxonomy by (Hafner and Mira da Silva 2023) is a theoretical foundation to define the essential functional and non-functional requirements. This taxonomy is utilised to derive theory-based requirements from academia, complemented by semi-structured interviews with eleven subject matter experts with experience ranging from four to 34 years. These interviews aim to enhance theory-driven requirements by incorporating insights from practitioners in real-world settings, specifically focused on German, Dutch, and Swiss enterprises across various sectors, as well as consulting environments (Hafner, Proper, and Mira da Silva 2024).

Phase 2 – Ontology capture and formalisation

In Phase 2, foundational reference ontologies are identified, applied, and expanded with concepts from the data valuation domain (Falbo 2014). The outcome of Phase 2 is a DVBC reference ontology in ArchiMate, which comprises identified and modelled elements as well as their relationships.

Conceptual modelling

The initial stage of the iterative conceptual modelling phase involves gathering, examining, and utilising existing knowledge in reference ontologies and conceptual models. These references are then applied and augmented to model a DVBC in ArchiMate. To clarify the resulting DVBC reference ontology, a glossary of terms and axioms that contribute to the CQs is established (Falbo 2014).

Review of existing ontologies and conceptual models. Reusing existing ontologies and ontological patterns is significant as they serve as valuable resources (Falbo 2014). The authors conducted a systematic literature review to analyse and extract the relevant patterns for determining data value (Hafner and Mira da Silva 2024). a DVBC taxonomy (Hafner and Mira da Silva 2023) and its practical validation (Hafner, Proper, and Mira da Silva 2024) based on the mentioned subject matter expert interviews in a prior study. The systematic literature review extracted 92 articles after abstract reading, in-depth analysis, and quality assessment. The findings revealed that while scholars from various domains have established fragmented approaches and frameworks for data valuation, no DVBC reference ontology exists.

To narrow the focus of this study towards developing a DVBC reference ontology, the authors conducted an additional literature analysis following Snyder (2019). This analysis aims to identify reference ontologies and concepts for modelling value in general, data value in particular, and capabilities in ArchiMate. To accomplish this, two search strings were utilised to analytically search for articles covering the above-mentioned topic within their titles. Web of Science was chosen as the database because of its comprehensive coverage, advanced search tools, and citation analysis capabilities.

While Query I ((TI=(Value)) AND TI=(Ontology OR ArchiMate OR 'Conceptual Model" OR "Reference Model")) aims at modelling value in ArchiMate (180 results), Query II ((TI=(capability)) AND TI=(Ontology OR ArchiMate OR "Conceptual results) Model" OR "Reference Model')) looks for modelling capabilities in ArchiMate (70 results). Upon completing the queries, the authors chose articles deemed appropriate in terms of content and provided applicable reference models with a suitable level of detail for developing the reference ontology (see Table 2).

Sales et al. (2019) have investigated value modelling in ArchiMate from a broad perspective. They developed the Value Pattern Language (VPL) based on the Common Ontology of ValuE and Risk (COVER). To achieve this, Sales et al. (2019) introduced specific

Table 2. Reference concepts based on the executed literature analysis.

Query	Authors	Title
I	(Sales et al. 2019)	A Pattern Language for Value modelling in ArchiMate
I	(Andersson et al. 2016)	Towards an Ontology of Value Ascription
I	(Gailly, Roelens, and Guizzardi 2016)	The Design of a Core Value Ontology Using Ontology Patterns
I	(Aldea et al. 2015b)	Modelling Value with ArchiMate
II	(Azevedo et al. 2015)	Modelling resources and capabilities in enterprise architecture: A well-founded ontology-based proposal for ArchiMate

value modelling patterns, such as Value Object, Value Experience, Value Subject, Value Event, Disposition, Causality, and Experience, as well as Object Valuation, and modelled them using generic structures. Therefore, the motivation, business, and strategy layers in ArchiMate were incorporated into the modelling. As the determination of data value is a subset of value in a broader sense (Khan, Uddin, and Gupta 2014), the VPL patterns are utilised as the foundation for developing a DVBC reference ontology in the context of this study.

Also, Aldea et al. (2015b) address the topic of modelling value in ArchiMate, utilising a higher level of abstraction than Sales et al. (2019). They incorporate value concepts into the business, motivation, strategy, as well as implementation and migration layers of an enterprise architecture. The work of Aldea et al. (2015b) is especially relevant for developing a DVBC reference ontology because it establishes a connection between value and capability. According to Aldea et al. (2015b), value realisation in general and thus the value realisation with and through data follows the attainment of a goal by a capability.

The fundamental ontology for value ascription by Andersson et al. (2016) differs from that of Sales et al. (2019) and Aldea et al. (2015b) as it is modelled using OntoUML, making it applicable for various modelling languages such as ArchiMate. Specifically, the work of Andersson et al. (2016) covers elements from the models of Aldea et al. (2015b) and Sales et al. (2019), such as perceived value and agents, also known as stakeholders. In addition, further elements such as cost- and benefit-specific valuation, which leads to the so-called theoretical value, are discussed. In our DVBC reference ontology, developed using ArchiMate, the authors have aligned the model with the value ascription ontology by Andersson et al. (2016) by including their concepts and applying them in conjunction with other pertinent literature on value modelling.

Moreover, Gailly et al. (2016) present an analysis of ontological patterns for representing value using UFO in their paper. The Value Measurement DROP pattern is of particular significance for developing a DVBC reference ontology, which illustrates the interplay between an agent's intentions and beliefs and the value measured based on the attainment of a goal.

Another reference paper by Azevedo et al. (2015) considered for developing a DVBC reference ontology deals with modelling resources and capabilities in enterprise architectures. It is essential to recognise that creating a DVBC reference ontology offers in-depth insight into the design of a capability. In contrast, the work of Azevedo et al. (2015) underscores how capabilities and resources interact with other elements in ArchiMate. Thus, while constructing the DVBC reference ontology, the specific elements of the metamodels suggested by Azevedo et al. (2015) are not employed as they are represented at a more abstract level. Nevertheless, for embedding a DVBC into an enterprise architecture, the concepts developed by Azevedo et al. (2015) are endorsed explicitly for consideration in future scientific efforts.

Application and reuse of existing ontologies and conceptual models. This study employs a comprehensive approach by integrating ontological reference patterns from literature (see Table 3), a previously conducted systematic literature review (Hafner and Mira da Silva 2024), as well as a previously designed DVBC taxonomy (Hafner and Mira da Silva 2023) and its validation (Hafner, Proper, and Mira da Silva 2024). This study can develop a robust DVBC reference ontology in ArchiMate by leveraging these resources.

Table 3. Reused concepts and elements for the DVBC reference ontology.[1]

	Reference models/ontologies		DVBC reference ontology	
Ref.	Concept	Representation	Applied concept	Applied represent.
[1]	Functional Goal	ArchiMate: Goal	Quantitative Data Valuation	Grouped Goals
[2]	Problem Solution	UFO: <<Goal>>	Qualitative Data Valuation	
[1]	Value Object	ArchiMate: Resource	Data Valuation Object, Data Type	Grouped Data Objects
[3]	Value Object	OntoUML: <<RoleMixing>>		
[1]	Value Object/ Enabler	ArchiMate: Resource	Framework and Method	Business Object
[1]	Value Experience	ArchiMate: Grouping	Data Valuation Process Component	Grouping
[4]	Business Actor	ArchiMate: Business Actor	Data Provider, Data Consumer, Data Broker, Independent internal Person, Independent external Person	Business Actor
[1]	Value Subject, Value Assessor	ArchiMate: Stakeholder	Data Value Determinator,	Business Role
[4]	Stakeholder	ArchiMate: Stakeholder	Data Value Auditor	
[3]	Agent	OntoUML: <<Category>>		
[2]	Recipient	UFO: <<Agent>>		
[1]	Value Event	ArchiMate: Business Process	Data Preparation and Contextualization, Data Value Assessment, Data Value Allocation, Data Value Prediction, Data Value Realization Data Value Monitoring, Change Management	Business Process
[3]	Perceived Value	OntoUML: <<Quality Kind>>	Sentiment and Perception	Business Object
[1]	Object Value	ArchiMate: Value	Business Value	Value
[2]	Value	UFO: <<Proposition>>		
[4]	Value	ArchiMate: Value		
[1]	Functional Goal Reward, Quality Goal Reward	ArchiMate: Goal	Desires and Preferences	Goal
	Satisfaction Level, Intention	UFO: <<Belief>>, <<Intention>>		
[3]	Desire, Preference	OntoUML: <<Quality Kind>>		
[1]	Capability	ArchiMate: Capability	Data Valuation Business Capability	Capability
[4]	Capability	ArchiMate: Capability		
[1]	Value Subject, Value Assessor	ArchiMate: Stakeholder	Top-Management, IT Domain, Legal and Risk Domain,	Grouped Stakeholders
[4]	Stakeholder	ArchiMate: Stakeholder	Finance Domain, Functional Domain	

(*Continued*)

Table 3. (Continued).

	Reference models/ontologies		DVBC reference ontology	
Ref.	Concept	Representation	Applied concept	Applied represent.
[1]	Functional Goal Reward	ArchiMate: Goal	Topline Growth and Market Share, Shareholder Value Max., Business Continuity and Risk Management, Process and Cost Optimization, Regulatory Compliance, Branding and Image, Data-Driven Product and Business Model Innovation, Fact-Based Decision Making, Strategic Partnerships, Fear of Competitive Disadvantages	Grouped Goal
[1]	Value Object/ Enabler	ArchiMate: Resource	Valuation Model/Application, Source Application	Application Component
[3]	Context	OntoUML: <<mixin>>	Context	Context
[2]	Caused State	UFO: <<Situation>>		
[3]	Theoretical Valuation, Relationship, Cost-/Benefit-Specific Valuation	OntoUML: <<Relationship Kind>>	Data Valuation Theory	Grouped Business Objects
[3]	Theoretical Value, Cost Value, Benefit Value	OntoUML: <<Quality Kind>>	Data Value Driver	Grouped Business Objects

Table 3 presents an overview of the ontological reference patterns and how they are tailored to fit the requirements of the study. This approach ensures that the DVBC reference ontology is both scientifically comprehensive and applicable in real-world enterprise settings.

The DVBC reference ontology, which was developed based on the above-mentioned ontological reference patterns (see Table 3), is illustrated in Figure 2. The model shows the in-depth view of a DVBC, which includes various structure and behavioural elements, according to ArchiMate (The Open Group 2019). The DVBC reference ontology consists of twelve logical clusters, specifically data valuation business capability, motivation, data valuation theory, data value driver, data valuation purpose, data valuation result, data valuation process component, tool, data valuation object, data type, stakeholder, and stakeholder domain. These clusters encompass components from an enterprise architecture's business, data, and application layers, augmented by the motivational extension of ArchiMate. Integrating both clusters and the modelled elements and their relationships collectively realise a DVBC for enterprises, as denoted by a realisation relationship to specify further the association relationship following Sales et al. (2019).

The core of the DVBC reference ontology is the behaviour elements representing the data valuation process components. Specifically, business processes are modelled following the ontological reference pattern provided by Sales et al. (2019). While data preparation and contextualisation, as well as data value assessment, are considered recommended mandatory steps in determining data value within a DVBC (Brennan, Attard, and Helfert 2018; Hafner and Mira da Silva 2023; Stein et al. 2021), other components of the data valuation process that may be triggered by demand can be optionally included (Jia, Li, et al. 2019; Holst et al. 2020; Debattista, Attard, and Brennan 2018; Brennan, Attard, and Helfert 2018; Hafner, Proper, and Mira da Silva 2024). Particular emphasis is placed by the interviewed subject matter experts on the accompanying change management process, as purposeful data valuation requires the readiness of the involved stakeholders and an implemented and ingrained data culture within the company (Hafner, Proper, and Mira da Silva 2024).

Further, for data valuation, the process components utilise data value drivers, theories, as well as frameworks and methods (Hafner and Mira da Silva 2024; Hafner, Proper, and Mira da Silva 2024). These are modelled as business objects, which are passive structure elements representing information that business processes can utilise (The Open Group 2019).

The data valuation theories provide the foundation for developing data valuation models and applications, which are modelled as application components in the application layer and may serve as vehicles to determine the data value within the process components. In addition, the tools grouping includes the source applications in which the objects to be valued are stored. Contrary to the reference pattern, according to Sales et al. (2019), data valuation objects are not modelled as resources but as data objects to emphasise that bundled or non-bundled data are subject to valuation. These bundled and non-bundled data valuation objects are ecosystem-agnostic, implying their applicability across a spectrum of data ecosystems. This includes both data valuation objects in constrained ecosystems with limited data and data valuation objects in expansive big data environments characterised by diverse data formats such as structured, semi-structured, and non-structured data, as well as significant data volume and volatility. Consequently, companies are encouraged to detail and structure the data valuation objects within the DVBC reference ontology based on their requirements and ecosystem factors. One possible way of structuring data objects to be valued pertains to the data type, which, based on the subject matter expert interviews conducted by (Hafner, Proper, and Mira da Silva 2024), is distinguished between master and metadata as well as transactional data.

However, data valuation, which helps solve real-world enterprises' challenges, cannot be solely driven by technology and theory. People are necessary to implement the DVBC and its process components (Hafner, Proper, and Mira da Silva 2024), modelled initially as stakeholders in the motivation layer by Sales et al. (2019). For this DVBC reference ontology, these people involved in the DVBC are represented as business actors and roles in the business layer. This is supported by the fact that the business roles of data value determinator and data value auditor within the DVBC not only have a vested interest in data valuation and specific requirements for it but also actively participate in the data valuation process (Holst et al. 2020). Specifically, the role of the data value determinator can be taken by data consumers, data providers, and data brokers, who can then directly execute the data valuation process. An alternative scenario offers the collaborative execution of data valuation through an interplay of the role of the data value determinator and the data value auditor, which independent internal or external business actors can take. While the data value auditor is assumed to be neutral, the data value determinator has desires and preferences based on the respective business context

(Andersson et al. 2016). These desires and preferences may also influence the choice of the underlying data valuation theories and data value drivers.

The aforementioned stakeholders, modelled as business actors due to their active role in the data valuation process, belong to stakeholder domains within an enterprise. The top-management, IT, legal and risk, finance, and functional domains were identified as particularly relevant by the interviewed subject matter experts (Hafner, Proper, and Mira da Silva 2024), and following Sales et al. (2019), they are modelled as stakeholders in the motivation layer.

Finally, the DVBC reference ontology contains the data valuation purpose and results, both realised through executing the components of the data valuation process. Ultimately, the outcomes of the data valuation process, be it relative or absolute data value, contribute to the creation of business value (Fleckenstein, Obaidi, and Tryfona 2023; Khan, Uddin, and Gupta 2014). The overarching motivations of stakeholders further shape the determination of the business value of enterprise data. According to insights from subject matter experts, these motivations encompass diverse aspects such as topline growth and market share, shareholder value maximisation, business continuity and risk management, process and cost optimisation, regulatory compliance, branding and image, data-driven product and business model innovation, fact-based decision making, strategic partnerships, and the fear of competitive disadvantages (Hafner, Proper, and Mira da Silva 2024). Following Sales et al. (2019), these motivations are modelled as goals within the motivation extension of ArchiMate.

Dictionary of terms and axiom definition

To make the DVBC reference ontology precise and to validate the requirements/CQs, Falbo (2014) recommends defining model components and deriving axioms (Table 4).

Discussion

To deepen the contextualisation of the DVBC reference ontology within existing literature, this paper discusses its content and methodology at this juncture. This examination aims to underscore the paper's robustness while shedding light on potential limitations.

Methodology-related discussion

One core objective of this study is to create a DVBC reference ontology as an artefact following design science research (Vom Brocke, Hevner, and Maedche 2020). Therefore, the systematic approach for building ontologies (SABiO) following Falbo (2014) was employed as a well-established methodology in ontology engineering within the information system research domain.

However, adherence to a recognised methodology does not inherently ensure the validity and applicability of an ontology. Therefore, this study followed the recommendations of SABiO and design science research to test and validate the developed artefact. Thus, the findings from eleven previously conducted subject matter interviews on applied ontological patterns were integrated into the DVBC reference ontology design and development, facilitating ex-ante validation. The ex-ante validation of the DVBC reference

Table 4. Contribution of groupings and associated axioms to the competency questions.

Grouping	Definition	Axiom	CQ
Data Valuation Purpose	Objectives of the DVBC.	Data valuation purposes can be quantitative and/or qualitative data valuation.	CQ2
Data Valuation Business Capability	An enterprise's ability to achieve the goal of data value determination while considering information, processes, roles, and resources (Hafner and Mira da Silva 2023).	Data valuation purpose influences the generation of business value.	CQ11
Data Valuation Object	The entity that requires valuation.	Data valuation objects can be bundled data (e.g. data products) or unbundled data (e.g. raw data points).	CQ3
		Data valuation objects can consist of different data types, such as master and metadata, as well as transactional data.	CQ4
		Data valuation objects are subject to the data valuation process components and can be accessed by the latter.	CQ10
		Data valuation objects imply a data value associated with a business value.	CQ11
Data Type	The class of data as an entity that requires valuation.	Data types can be master and metadata or transactional data.	CQ4
		Data types can form data valuation objects, such as bundled and non-bundled data.	CQ3
		Data types are subject of the data valuation process components and can be accessed by the latter.	CQ10
Motivation	The overarching goals of stakeholders in an enterprise that are placed in a data valuation business capability.	The motivations may encompass economic, legal, reputational, compliance, innovation, technology, and business aspects.	CQ1
		The motivations depend on the various stakeholders' context, desires, and preferences.	CQ1
		Diverse stakeholders may possess varying motivations regarding a data valuation business capability, which can be competing or complementary.	CQ1
		The motivations influence the purpose and result of data valuation, as well as the selection of data value drivers and theories.	CQ1
Data Valuation Result	Outcomes generated by the application of the DVBC and its patterns.	Data valuation results can be either the determination of a relative data value or an absolute data value, which can be of approximated or specific nature.	CQ11
		The determined data value contributes to the realisation of the respective business value.	CQ11
Data Value Driver	Factors that affect the value of data.	Data value drivers positively, negatively, or neutrally influence the data valuation objects and their value.	CQ5
		The drivers may encompass business-related, data- and technology-related, and perceived aspects.	CQ5
		Data valuation process components access data value drivers to determine the value of data valuation objects.	CQ10

(*Continued*)

Table 4. (Continued).

Grouping	Definition	Axiom	CQ
Data Valuation Process Component	The components of a process through which data value is determined.	Data valuation process components include two mandatory components (preparation and contextualisation, assessment), followed by optional components (allocation, prediction, monitoring, and change management).	CQ10
		Data valuation process components realise the purpose of the data valuation business capability and its results.	CQ10
		Data valuation process components utilise the data value drivers and theories to determine data value.	CQ10
Tool	The applications and models utilised in the DVBC and their related process components.	Tools include valuation models and applications as well as frameworks and methods, which serve as elements to support determining data value, and they include source applications, which serve as passive elements storing the data valuation objects of different types.	CQ7
		Valuation models and applications access data valuation objects and types as input for data value determination.	CQ7
		Models and applications apply data valuation theories as the algorithmic backbone of their functionalities.	CQ7
Data Valuation Theory	Concepts that underlie frameworks, algorithms, and approaches for determining data value.	Data valuation theories originate from scientific domains such as economics, mathematics, and informatics or are proprietary.	CQ6
		Scientific domains belonging to data valuation theories consist of one or more subdomains.	CQ6
		Data valuation process components access data valuation theories to determine the value of data valuation objects.	CQ10
Stakeholder	Individuals or groups interested in or actively participate in the DVBC.	Data value determinators can execute the valuation process components alone or with data value auditors.	CQ9
		Data value determinators have sentiments, perceptions, desires, and preferences influencing the value drivers and theories, while data value auditors are assumed to be neutral.	CQ9
		Personal/professional contexts influence the desires and preferences of data value determinators.	CQ9
Stakeholder Domain	Areas within a company from which relevant business actors for data valuation are consulted.	Stakeholder domains imply functional, technological, and strategic areas across various hierarchy levels within an enterprise organisation.	CQ8
		Internal data value determination/auditing stakeholders belong to an enterprise's stakeholder domain.	CQ9

ontology posed challenges such as identifying suitable subject matter experts, conducting interviews in a remote setting, and establishing a unified understanding of terminologies used during the interviews. To locate appropriate interviewees, factors for selection were utilised, including a minimum experience period of at least three years, a thematic focus on data value or enterprise architectures, and the exclusion of interviewees from the same organisation to obtain a broad perspective on the subject matter. During the ex-ante validation, a camera-on policy was enforced in interviews to perceive both verbal and non-verbal communication, allowing adjustments to the conversation flow if necessary. Additionally, clarifications were made regarding terminologies in case of misunderstandings and incorporated into the reference ontology (Hafner, Proper, and Mira da Silva 2024). This validation process ensures coverage of ontological patterns that are considered significant from both scientific and real-world practitioner perspectives. Nevertheless, it is essential to acknowledge that the absence of ex-post validation may introduce some level of ambiguity in the DVBC reference ontology. This ambiguity, however, is deemed acceptable as the DVBC reference ontology is designed to be adaptable and extendible to the specific requirements of an enterprise.

The choice of an appropriate modelling language for the DVBC reference ontology posed a challenge, as it depended on the desired level of detail, the target audience of the reference ontology, and the prevalence of usage of the modelling language. Due to the fragmented nature of data valuation landscapes, the defined level of detail of the DVBC reference ontology is at an enterprise architecture level, focusing on the main process level, stakeholders, the motivation and purpose of data valuation, as well as generic data value drivers and theories. This level of abstraction mainly targets professionals involved in developing and managing a DVBC, such as enterprise architects, CIOs, CDOs, and data strategy professionals. On the other hand, the DVBC taxonomy targets scholars in the fields of value modelling and ontology engineering. Considering these factors, ArchiMate with its underlying meta-model was chosen for the DVBC reference ontology. While ArchiMate offers advantages such as its applicability in both scientific (Al-Turkistani, Aldobaian, and Latif 2021; Aldea et al. 2015b; Bui 2017) and practical contexts (Cameron and McMillan 2013), its accordance with other scientific value-related reference ontologies, as well as its structured approach aligning with the TOGAF layers, it also presents limitations that merit consideration. Specifically, the DVBC reference ontology developed using ArchiMate, particularly the relationships among components, can only be represented at a relatively high level of abstraction. Thus, achieving a more granular level of detail in the DVBC reference ontology necessitates considering cardinalities between components, depending on the enterprise's specific use case. Consequently, alternative capable modelling languages and meta-models such as the Unified Foundational Ontology (UFO) following Guizzardi et al. (2022), the Unified Modelling Language (UML) following ISO/IEC (2012) or the function-context-behaviour-principle-state-structure framework (FCBPSS) in a system engineering context following (J. W. J. W. Wang et al. 2016; W. J.; W. J. Zhang and Wang 2016) offer their raison d'être for detailing and extending the DVBC reference ontology, warranting exploration in future research endeavours.

In summarising the methodology-related discussion, it can be asserted that the DVBC reference ontology is deemed scientifically sound and robust, as it adhered to well-established and recognised methodologies and underwent ex-ante validation. It is acknowledged that the DVBC reference ontology allows room for further development by utilising alternative validation and modelling methods.

Content-related discussion

Apart from the discussion concerning methodology, it is imperative to subject the contents of this study to critical analysis. The developed DVBC reference ontology considers and includes commonly used ontological reference patterns (Aldea et al. 2015b; Andersson et al. 2016; Azevedo et al. 2015; Gailly, Roelens, and Guizzardi 2016; Sales et al. 2019) to answer two research questions about the components of data valuation within the context of a business capability and their relationships.

The reference patterns are partially modified to fit the study's objectives, but their contextual substance remains valid. The reason for the adjustment of the ontological reference patterns is that the variety of five considered reference papers containing many ontological reference patterns implies diverse abstraction levels combined with several modelling techniques. Combining the ontological reference patterns and creating the DVBC reference ontology as a new artefact aligns this study with the existing domain knowledge of value modelling. To ensure that the adaptation of the ontological reference patterns does not contradict the state of the art of scientifically validated concepts and, simultaneously, to set quality standards for the DVBC reference ontology, requirements are defined based on Falbo (2014).

The formulated functional requirements, presented as CQs, as well as the non-functional requirements, are compared with the developed DVBC reference ontology. Table 4 proves that the formulated axioms, which describe the DVBC reference ontology, address all formulated CQs. Thus, it can be verified that the DVBC reference ontology meets all functional requirements. Additionally, the non-functional requirements can also be considered as satisfied. This can be justified because the applied ontological reference patterns ensure interoperability standards (NFR3). Further, using ontological reference patterns supports the usability and expandability of the DVBC reference ontology (NFR1). Finally, the reference ontology considers existing literature on data value approaches, models, and taxonomies, which satisfies NFR2.

In concluding the content-related discussion, it can be affirmed that the DVBC reference ontology successfully bridges the gap between theory and practice, as it draws upon both relevant scientific publications and eleven interviews with subject matter experts from real-world settings as a basis for modelling a DVBC.

Conclusion

Data value and its determination have been extensively studied and modelled in scientific literature. Nevertheless, the systematic modelling of data valuation as an actively managed and governed data valuation business capability (DVBC) has not yet been carried out. Thus, enterprises continue to face challenges in determining the value of their data, thereby impeding data monetisation potentials, and consequently limiting their future competitiveness. Therefore, this study contributes to closing the research gap of modelling data valuation as a business capability through the lens of an enterprise architecture following TOGAF.

The crafted artefact, a DVBC reference ontology, was constructed utilising the systematic approach for building ontologies (SABiO). The DVBC reference ontology comprises twelve groupings, 66 components and 67 relationships. Therefore, pertinent ontological reference patterns from academic research are employed in the design of the DVBC reference ontology. Moreover, the application of ArchiMate and TOGAF, utilised as architectural modelling language and framework, respectively, is endorsed due to their acknowledgement as best practices in both academic research and practical industry settings. This endorsement guarantees the applicability of the DVBC reference ontology across academia and real-world enterprises.

Overall, this study has three core implications for academia, specifically the research areas of information systems and data management. Firstly, the developed artefact extends the research streams of modelling value in general by detailing the generic concepts in a data-related context as a foundation for further exploration, as recommended by scholars. Secondly, the DVBC reference ontology integrates frequently encapsulated approaches into a comprehensive and intertwined framework considering business and technology-driven elements crucial for data valuation. Thirdly, the DVBC reference ontology enhances an established DVBC taxonomy by including additional elements pertinent to practical contexts, elucidating their relationships. This contributes to an improved comprehension of data valuation in academia and practice, making data value determination applicable in a broader sense. This convergence between science and practice also implies two implications for real-world enterprises.

Firstly, the DVBC reference ontology provides a framework for enterprises to streamline their data valuation efforts towards an actively managed and comprehensive business capability, which may be embedded systematically in their enterprise architecture. Incorporating a DVBC in daily enterprise processes and integrating it into enterprise architectures can act as a catalyst for generating value with and through data, fostering future competitiveness. Secondly, owing to the interdisciplinary nature of data valuation involving various business- as well as data or technology-related elements, the DVBC reference ontology aids enterprises in identifying relevant components, assessing their maturity, and optimising them. This is crucial for implementing data valuation not merely as a necessary function but as a strategically sustainable capability.

This study, including the DVBC reference ontology, also has limitations. One limitation relates to the abstraction level of the DVBC reference ontology, which is modelled to a conceptual degree to illustrate the main components and their relationships.

Therefore, additional work to be conducted in the upcoming year is necessary to elaborate on the components and relationships within the DVBC reference ontology, including cardinalities, to foster practical applicability and root the model in foundational ontologies, such as Unified Foundational Ontology (UFO) among others (Guizzardi et al. 2022). Moreover, ArchiMate is the modelling language of choice due to its frequent application in science and practices. Nonetheless, every modelling language has its drawbacks, such as specific components and relationships that cannot be modelled or can only be modelled suboptimal. Hence, the DVBC reference ontology can be validated and improved in future research using alternative modelling languages that suit different purposes and target audiences. Moreover, the dynamic interaction among individuals, technology, and data inherent in the DVBC implies an arbitrarily high complexity. Therefore, an additional aim for future research may be the exploration of a DVBC from an enterprise systems standpoint, utilising domain modelling frameworks such as FCBPSS (J. W. J. W. Wang et al. 2016; W. J.; W. J. Zhang and Wang 2016), among others, while specifically focusing on the interrelation among the diverse factors contributing to the complexity of data valuation. Further, the DVBC reference ontology is designed at an enterprise architecture level, meaning that the precise process steps to determine data value are only partially representable. Therefore, ongoing research applies specific data valuation theories, such as decision theory, to model necessary process steps and test them within the frame of the DVBC reference ontology. Finally, the DVBC reference ontology was validated using an ex-ante approach, ensuring that only ontological patterns relevant to scholars or professionals are included. However, to further validate the DVBC reference ontology, ex-post validation is intended as the immediate next research step, e.g. by challenging the DVBC reference ontology in case studies with real-world enterprises. In this context, while DVBC is regarded as agnostic to ecosystems, it is also advised to subject the DVBC to analysis concerning its applicability within big data ecosystems of real-world enterprises, where the DVBC could encounter obstacles such as the significant volume and velocity of both structured and unstructured data, among other factors. In addition to the ex-post validation of the DVBC reference ontology, which is particularly relevant for reaching the target audience of enterprise architects, CIOs, CDOs, and data strategy experts further social networks such as *LinkedIn* and research platforms like *ResearchGate* are utilised for disseminating the DVBC reference ontology. These platforms facilitate gathering additional feedback for further development.

Note

1. To simplify the table, references are abbreviated as follows: Aldea et al. 2015b; Andersson et al. 2016; Gailly, Roelens, and Guizzardi 2016; Sales et al. 2019.

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