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A decision-support model for data product valuation in the energy sector: A multi-criteria perspective

Markus Hafner ^{a,b}, Miguel Mira da Silva ^b, Mónica D. Oliveira ^{a,c}, Frederico Cabral^d and Henderik Alex Proper ^e

^aCentre for Management Studies (CEGIST), Instituto Superior Técnico, Lisbon, Portugal; ^bINESC, INOV, Instituto Superior Técnico, Lisbon, Portugal; ^ciBB-Institute for Bioengineering and Biosciences and i4HB-Associate Laboratory Institute for Health and Bioeconomy, Instituto Superior Técnico, Lisbon, Portugal; ^dData and Analytics, Galp Energia SGPS S.A, Lisbon, Portugal; ^eBusiness Informatics, TU Wien, Vienna, Austria

ABSTRACT

Determining the value of data products remains a challenge for enterprises and academia, despite the growing recognition of data as a strategic asset across their business operations. This complexity arises from varying definitions of data value, diverse stakeholder perspectives, and the interdisciplinarity of data valuation. To address these challenges, this study develops a multi-criteria evaluation model based on the MACBETH approach to help Galp Energia, a Portuguese energy company, assess the value of data products in its renewables division. The developed model incorporates seven criteria across an enterprise architecture's business, data, and application/technology layer, providing a comprehensive assessment of five data products. The study contributes to the literature by proposing a tailorable data valuation approach that may be applicable to other industries. Beyond quantifying the data product value, the resulting model serves as a managerial tool to support data-driven decision-making. The model is constructed using a robust approach and overcomes the limitations of existing models, such as oversimplification and practical implementation challenges. Additionally, it fosters interdisciplinary collaboration between research and industry. Future research directions include using the model as a foundation for developing modular data valuation frameworks, exploring its application across sectors, and integrating cross-sector benchmarks.

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1. Introduction

'If you cannot measure it, you cannot control it. If you cannot control it, you cannot manage it' (Harrington, 1991, p. 164). Measuring and managing the value of data, commonly known as data valuation, has gained significant attention from scholars and enterprises transforming into data-driven organizations (Brennan et al., 2018; Fleckenstein et al., 2023; Hafner et al., 2024; Li et al., 2019; Lim et al., 2024; Liu et al., 2024; Meierhofer et al., 2022; Wang et al., 2022; Wu et al., 2022; Zhou et al., 2024), yet it is rarely implemented using robust, transparent, and reproducible methods in practice. However, data valuation extends beyond merely assigning a potential monetary price tag to data. Data valuation serves as a critical foundation for promoting data sharing and trading, particularly in emerging data-centric ecosystems, such as those in the energy sector (Wang et al., 2021). Moreover, data holds substantial commercial value (Xiong & Zheng, 2019), not only in terms of monetization but also in enabling fast and fact-based (investment) decision-making (Mahmood et al., 2023; Schneider et al., 2023), especially in the presence of resource constraints.

Despite the significant benefits of data valuation, many enterprises, including Galp Energia (Galp), a Portuguese energy company, face the challenge of proper data value chain management (El Kadiri et al., 2016) including measuring the value of their data (Li et al., 2019; Meierhofer et al., 2022). This limitation hinders their ability to effectively control and manage the data-related activities derived from it, as outlined in the statement by Harrington (1991). This is

emphasized in the field study by Meierhofer et al. (2022, p. 10), which highlighted 'that most companies still lack theoretical and practical tools for quantifying the value of the data in their ecosystem.' A fundamental factor contributing to this challenge is that 'relatively few studies on the valuation of data assets [exist], in which theoretical exploration is difficult to meet practical needs' (Li et al., 2019, p. 92). El Kadiri et al. (2016, p. 29) present this in a broader context through their assumption that 'specifically, technologies related to [...] data value chains, are now recognized as having passed the stage when they were considered as a frontier technology and have become acknowledged as a set of capabilities that must be pervasively incorporated across enterprise functions and operators.'

These practical needs encompass three key dimensions: a) the value of data is shaped by multiple interrelated factors, which include business-driven factors, such as business utility and the costs associated with data management; data- and technology-driven factors, including information potential, computational efficiency, data quality, data security, and the capabilities of related applications; and subjectivity-driven factors, such as the perceived data value by various stakeholders (Hafner et al., 2024; Noshad et al., 2021); b) considering the multitude of factors influencing data value, it is crucial for enterprises to assess data value at a proper level of detail (Cong et al., 2022; Sidgman & Crompton, 2016), ensuring reliable and actionable results while maintaining a proportionate allocation of resources; c) diverse perspectives and requirements of stakeholders regarding data and its value necessitate their integration into the data valuation

process to ensure their viewpoints and needs are appropriately addressed (Cong et al., 2022; Liang et al., 2018).

Academia has been striving to develop models and frameworks to address these challenges. However, scholars in the field of data valuation have been emphasizing 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’ (Wu et al., 2022, p. 1), and that ‘data value monitoring infrastructure; formal models describing metrics, dimensions, and how they relate’ (Brennan et al., 2018, p. 582) are required.

This paper aims to address the identified research gap by developing a multi-criteria data product valuation model with the MACBETH (Measuring Attractiveness by a Categorical Based Evaluation Technique) multi-criteria value measurement approach (Bana et al., 1994; Bana e Costa, De; Quartel et al., 2012), which has been widely used in the last two decades across various areas of application (Ferreira & Santos, 2021). Therefore, this paper is guided by the research question: *How can the value of data products be systematically determined while accounting for multiple criteria, diverse stakeholder perspectives, and uncertainties?* The specific aim is to develop a requisite model, as defined by Phillips (1984), to assist the renewables division of Galp in reflecting on data value and measuring the value of data products, defined as context-specific information bundles (e.g. models, algorithms, datasets) crafted to provide value to consumers (Huang et al., 2015; Trenevskaja Blagoeva & Mijoska, 2019; Wang et al., 2021). The developed model offers three core benefits: First, it employs a scientifically robust and user-friendly approach, specifically MACBETH, which fulfills Galp Energia’s requirements by achieving an optimal balance between scientific rigor and efficient model development and execution. Second, it establishes a best practice and a source of inspiration for data valuation that can be applied across various industries and sectors, as identified through expert interviews with experienced stakeholders from the automotive, manufacturing, financial services, media, government, and technology industries. Third, it contributes to fostering interdisciplinary dialogue between research domains and real-world enterprises and promoting educational awareness in the context of data value, as requested by Ramadan et al. (2024).

The paper is structured as follows: Section 2 provides an overview of the research background, focusing on key terminologies and existing literature addressing evaluations with multiple criteria in the context of data valuation. Section 3 outlines the theoretical foundations of the adopted methodology and the construction of the Galp data valuation model. Section 4 presents the results before Section 5 discusses the findings, implications, and avenues for future research. Finally, Section 5.1 presents concluding remarks.

2. Literature background

This section presents core concepts and terminology, specifically data value and data products, as well as studies that have explored data value through multidimensional approaches.

2.1. Data value and data products

While the significance of data value is widely acknowledged in both academia (Coyle & Manley, 2023; Kang & Guo, 2023) and across various industries, including the energy sector (Janev et al., 2022; Liu et al., 2024; Thieullent et al., 2020; Wang et al., 2021; Zhou et al., 2024), its precise definition often remains ambiguous. This challenge becomes particularly relevant when employing approaches to assess data value in multiple dimensions, considering various stakeholder perspectives and encompassing not only a quantitative but also a qualitative and even an emotional dimension (Attard & Brennan, 2018; Brennan et al., 2019; Grover et al., 2018; Hafner, Mira da Silva, et al., 2025; Meierhofer et al., 2022).

One of the most prominent conceptualizations of data value is its economic value, referring to the economic impact of data when utilized in business operations. Additionally, data value can be understood from a socio-ecological perspective, referring to its influence on broader societal and environmental contexts (Attard & Brennan, 2018; Meierhofer et al., 2022). Furthermore, data possesses functional value, as it can facilitate fact-based decision-making and expand the functional capabilities of a product (Grover et al., 2018; Meierhofer et al., 2022). Lastly, data value may also be subjective or perceived, particularly in the case of sensitive information, such as personal data (Baird & Raghuram, 2015; Brennan et al., 2019; Fehrenbach & Herrando, 2021).

Alternative conceptualizations of data value have been proposed through the 3 V and 7 V frameworks. Within the context of big data, the 3 V model characterizes data value as emerging from the interplay between velocity, variety, and volume (Laney, 2001). This perspective was later expanded into the 7 V model, which adds the dimensions of veracity, validity, and volatility, while positioning value itself as a distinct and integral component of the framework (Khan et al., 2014). Other, more technology-oriented definitions of data value frequently focus on domains such as artificial intelligence (AI), where value is assessed in relation to factors like data quality, associated costs, and the resulting performance of AI models (Schneider et al., 2023; Xu et al., 2022). In contrast to this application-driven view, alternative interpretations draw on entropy-based approaches. Within this paradigm, data value is defined by its ability to reduce uncertainty, particularly in complex decision-making scenarios. From this perspective, the greater the contribution of data to uncertainty reduction, the higher its perceived value (Wang et al., 2021).

The diverse conceptualizations of data value, its inherent complexity, and the subjectivity in its determination can increase the degree of uncertainty in data valuation (Hafner, Mira da Silva, et al., 2025). According to Stewart and Durbach (2016, p. 468), uncertainty is a situation in which ‘a person does not possess the information which quantitatively and qualitatively is appropriate to describe, prescribe or predict deterministically and numerically a system, its behavior or other characteristics.’ Consequently, uncertainties may arise during data value determination, whether in selecting appropriate methods and models (including the underlying data) or in assessing data value. They should ideally be mitigated and minimized through a suitably chosen approach. In summary, the value of data is highly context-dependent (Brennan et al., 2018;

Ebiele et al., 2025; Ghorbani et al., 2020; Kakuschke et al., 2025, 2025; Stein et al., 2021), extends beyond mere economic valuation or assigning a price tag to a dataset, and its determination requires appropriate approaches that consider various perspectives and address potential uncertainties (Hafner, Mira da Silva, et al., 2025).

However, the fundamental question remains: how can the data value of any type be effectively captured? Two essential components are required to address this: an appropriate methodology and a bearer that holds data value. One bearer of data value can be data products, encompassing any form of valuable information that possesses clear ownership, defined scope, and structured format, making it accessible to data consumers (Hasan & Legner, 2023; Huang et al., 2015; Rix et al., 2021; Trenevskaja Blagoeva & Mijoska, 2019).

Since a data product can serve as a bearer of value, it may offer several potential advantages, such as gaining competitive advantages (Trenevskaja Blagoeva & Mijoska, 2019), improved decision-making, enforcing data governance, minimizing the time to insight, and properly accessing data (Hasan & Legner, 2023). Rix et al. (2021) argue that data products may evolve into commercial goods themselves or be offered as supplements to an enterprise's product portfolio, making them commercially available (Trenevskaja Blagoeva & Mijoska, 2019). To deliver value, one or many data product consumers are required. These consumers may have requirements that, when fulfilled, lead to increased data product value (Hasan & Legner, 2023).

Data products can take various forms, including application programming interfaces, online streams, static data collections, contextualized datasets (Fricker & Maksimov, 2017; Hasan & Legner, 2023; Wang et al., 2021), algorithms, retro- and prospective models (Hasan & Legner, 2023; Trenevskaja Blagoeva & Mijoska, 2019; Wang et al., 2021), diagrams, dashboards (Huang et al., 2015), and others. Building on this definition, in the context of this study, data products refer specifically to analytics services owned and managed by the Galp data and analytics team, which are provided to consumers within Galp's renewables business units.

Given the identified challenges in data valuation, multi-criteria data valuation is a good fit for determining data value. Therefore, applying an appropriate methodology is essential to capture this complexity and accurately determine the value of data products. Hafner et al. (2024) propose a reference ontology for data valuation business capabilities, in which data valuation is described as the process of preparing and contextualizing data into data products, assessing their value, implementing them, and monitoring both the products and their value contribution to relevant stakeholders. A critical aspect of data valuation is data value determination or assessment, which can be conducted through multi-criteria evaluation, as further elaborated in the following section.

2.2. Modeling multiple criteria in the context of data value

Modeling multiple criteria encompasses a range of approaches designed to assist decision-making in contexts characterized by numerous objectives, thereby incorporating a diverse spectrum of evaluative dimensions, including business imperatives, technological considerations, sentimental factors, data-driven insights, societal impacts, and regulatory

compliance (Barham & Daim, 2020; Sachdeva et al., 2016; Si & Qin, 2020; Si & Xiao, 2020), while involving relevant stakeholders. By synthesizing these varied perspectives, the Multi-Criteria Decision Analysis (MCDA) field facilitates a more nuanced, holistic assessment, enabling informed and balanced decision-making in multifaceted environments (Belton & Stewart, 2002; De Montis et al., 2004). To the best of the authors' knowledge, MCDA is not commonly used to assess the value of data products. Still, it has been used in related decision-making domains, such as data quality management (Si & Qin, 2020), data project management (Barham & Daim, 2020), and cloud solution engineering (Sachdeva et al., 2016).

Among methods used to deal with multiple criteria (although not necessarily framed in multi-attribute value theory and in multi-criteria value measurement (Belton & Stewart, 2002)), AHP has been applied in related contexts, often combined with other methods. For instance, AHP has been used in the selection process for product-service systems in combination with elements from Concept Design Analysis (CODA) (Bertoni, 2019). In this context, criteria such as quality, resource allocation efforts (including cost and time), and sustainability were employed to guide decision-making to the extent to which physical products should be augmented with additional services.

In another study, AHP was combined with the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) for building a data product quality evaluation model (Si & Qin, 2020). The model integrates criteria such as data accuracy, integrity, timeliness, and uniqueness, among others, aligning these criteria with industry-recognized standards, including the Data Management Body of Knowledge (Dama International, 2017), which facilitates the assessment of the quality level of data products.

TOPSIS has been used by Sachdeva et al. (2016) to identify suitable cloud solutions for data projects, with criteria such as business continuity and security being deemed as relevant, and Alidrisi (2021) combined TOPSIS with the fuzzy Analytic Network Process (ANP) and Interpretive Structural Modeling (ISM) for assessing the value of green supply chain management practices. In this case, the focus was centered on five V's of big data: veracity, velocity, value, variety, and volume (Khan et al., 2014; Laney, 2001).

Another TOPSIS-based framework relevant as related work is proposed by Pramanik et al. (2020) for selecting information system projects. In this model, the projects constitute the decision alternatives and are assessed according to four criteria: organizational behavior, project quality, applied technologies and innovations, and hardware and software investment costs. The evaluation is conducted using a 7-point linguistic scale ranging from *very bad* to *very good*.

Beyond TOPSIS, several other related approaches exist. Barham and Daim (2020) employed Hierarchical Decision Modeling (HDM) to evaluate the maturity of smart cities in executing their data projects by analyzing key criteria across organizational, technological, and legal perspectives. For instance, the people perspective includes public acceptance and employee skills. The technology perspective covers criteria such as data availability and data complexity. The legal perspective addresses data security, privacy, and ownership. The organizational perspective considers criteria such as management support and data strategy.

Another approach to modeling various criteria for determining data value is proposed by Fleckenstein et al. (2023). In their scoring model for data valuation, various criteria, including data quality, volume, and variety, are assessed through survey questions. Respondents can select predefined answers, each of which is associated with a specific point value. These points are then multiplied by corresponding weights to calculate weighted scores.

In addition to specific studies that model multiple criteria in the context of data valuation, Ebiele et al. (2025) conducted a literature review to classify quantitative data valuation approaches. This review also highlights that, while techniques such as TOPSIS, fuzzy expert systems, weighted product or weighted sum models, and advanced arithmetic operations have been applied in individual cases, it becomes evident that MACBETH and other constructive approaches built upon value measurement principles have not yet been utilized in the context of data valuation. Furthermore, the literature review shows that quantitative data valuation has primarily focused on game-theoretic approaches, although methods modeling multiple criteria are gaining increasing popularity. The combination of the growing relevance of MCDA approaches in the context of data valuation, as well as the absence of value-based and socio-technical approaches, such as MACBETH, in this field underscores the relevance of this paper in addressing an existing research gap.

In addition to MCDA-related approaches for modeling multiple criteria in the context of data value, several research groups with a stronger focus on modeling have addressed the topic from a taxonomic or ontological perspective. A relevant taxonomy in this regard is the decision-making data value taxonomy proposed by Lega et al. (2022), which distinguishes between two main components of data value: data quality and data utility. Both components can be further broken into measurable criteria. In this taxonomy, traditional data quality criteria such as completeness and correctness are considered alongside utility-related criteria such as ease of use and legal aspects.

Ontological approaches to modeling multiple criteria in the context of data value have been presented, for example, by Sales et al. (2018, 2019). Through their ontological descriptions, these authors demonstrate that value is not necessarily tied to an object itself, but rather to the experience that a consumer derives from using the object. This perspective implies that the inclusion of subjectively perceived criteria is of critical importance in the context of data value.

When examining both MCDA-centered and modeling-centered literature, it becomes evident that the representation of multiple criteria in the context of data value is a significant topic with growing research momentum. However, although no approaches have been identified that explicitly focus on evaluating data products, it is necessary to draw parallels between the criteria used in adjacent studies, as these may influence the perceived value of data products. For instance, key criteria clusters of data product value can be identified across various clusters, including business considerations (e.g. project time and costs for developing data products) (Ghosh et al., 2017; Hafner et al., 2024, 2025), data management (e.g. data quality and security), legal aspects (e.g. information privacy), and technology-related factors (e.g. the availability of tools and technologies for data

product implementation), as highlighted by Hafner et al. (2024, 2025).

3. Methods

This section lays the methodological foundations for building a model using the MACBETH approach for multi-criteria value measurement, to assist Galp in determining the value of its data products. Specifically, this section structures the data product evaluation problem, including stakeholder identification along with their respective objectives. Furthermore, the multi-criteria data product valuation model is structured, involving the development of a value tree, the construction of criteria and of descriptors of performance, the establishment of data product alternatives, and the mapping of alternatives' performance. Finally, the evaluation model is constructed, incorporating value functions, criteria weights, and being hardened for sensitivity and robustness analyses.

To assess the generalizability and transferability of the developed multi-criteria data product valuation model to other enterprises and sectors, insights from comparing the model results with experts' views collected through interviews in a different study are taken (see Discussion Section 5.1). These semi-structured interviews were conducted and transcribed as part of a related study by Hafner, Mira da Silva, et al. (2025) and enable reflecting upon the areas of concern and criteria built upon data value assessment. In fact, 11 interviewees represented a broad range of sectors, including consulting, media, government, automotive, manufacturing, financial services, and technology, across Germany, Switzerland, and the Netherlands. This significantly extends the focus of the present study, which is centered on one enterprise in the Portuguese energy sector.

3.1. Methodological overview

To build a data value model to assist Galp, this study selected the MACBETH socio-technical approach, which is rooted in the principles of multi-criteria value measurement and respects multi-attribute value theory (Belton & Stewart, 2002) MACBETH has been extensively used to tackle complex real-world problems (Bana, DE Corte, et al., 2012; Belton & Stewart, 2002; Ehrgott, 2005; Franco & Montibeller, 2011). It follows a socio-technical paradigm in which sound protocols of questioning and value measurement tools are combined with fit-for-purpose participatory processes, so that a data value model can reflect the perspectives of those involved in the model-building process (Phillips et al., 2007). MACBETH adopts a friendly protocol of questioning in which evaluators firstly provide ordinal information, then offer qualitative judgments on the difference in attractiveness between different levels of performance, and finally, MACBETH assists in converting qualitative judgments into quantitative cardinal value scores (Angelis & Kanavos, 2017; Bana et al., 2003, 2012; Fasolo et al., 2014), so that the model can undergo further testing and adjustments.

Further to its methodological robustness, MACBETH offers three key advantages: a) a high informational depth by collecting not only ordinal and qualitative judgments but assisting to convert those judgments into cardinal scales of value, b) the construction of reusable and transparent

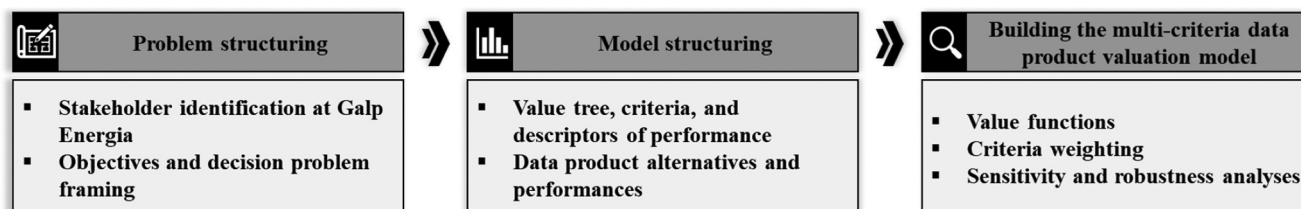


Figure 1. Adopted MCDA process (steps and tasks described in the following subsections).

models, and c) a low barrier to entry for organizations with limited quantitative data to inform model building, supporting the decision to apply MACBETH for the valuation of data products at Galp.

For the social component of multi-criteria value modeling at Galp, two data valuation workshops, a structuring workshop (onsite), and a refinement workshop (remote) were conducted and recorded after consent to guide stakeholders through the three main steps of multi-criteria modeling (see Figure 1, adapting Bana et al. (2005), and Franco and Montibeller (2011)): Defining and structuring the problem, structuring the value model, as well as building (and testing) the multi-criteria data product valuation model. Further details on the applied MCDA process are available in Table A6 in the Appendix.

The initial step, *problem structuring*, is critical for comprehensively understanding the multi-criteria problem (Bana et al., 1999; Franco & Montibeller, 2011). This step focuses on identifying key stakeholders, analyzing their objectives, and collaboratively framing the multi-criteria problem, such as valuing potential data products to be developed, considering multiple criteria.

The second step, *model structuring*, involves representing the areas of concern and criteria (together with associated descriptors of performance) within a value tree (Bana et al., 2005; Bana, DE Corte, et al., 2012). Structuring the value tree entails decomposing the overarching model objective into sub-objectives using a value-driven, top-down approach. The primary goal is to define criteria accurately, clearly depicting the stakeholders' objectives, and operationalizing each criterion through a corresponding performance descriptor. In line with building an additive value model (the most commonly developed in the literature and in real settings), criteria should be constructed so that they satisfy the preference independence conditions, which enable the partial value of decision alternatives to be assessed for each criterion separately. Additionally, the decision alternatives, in this case, data products to be evaluated, are identified, and their performance in each criterion is described (Bana et al., 2005; Franco & Montibeller, 2011).

The third step, *building the multi-criteria data product valuation model*, involves building value functions and weighting criteria through the MACBETH approach (details about the MACBETH approach can be found in (Bana et al., 2016; Bana, DE Corte, et al., 2012)). Value functions and weights enable transforming data products' performance into partial and overall value, respectively. The M-MACBETH software assists in model development (Bana et al., 2017). In view of evaluating the overall value of data products in a common metric, the evaluation model is built to have the following additive structure:

$$V_i = \sum_j w_j v_{ij}(p_{ij}) \quad (1)$$

Let V_i ($V_i = 0, \dots, 100$) represent the overall attractiveness of a data product i , in this case, the value of a data product. Let w_j ($w_j > 0$) denote the weight coefficient of a criterion j , and v_{ij} represent the partial value of a decision alternative i with respect to a specific criterion j and with performance p_{ij} . For promoting model interpretability and intelligibility, the following reference performance levels were adopted for each criterion j (following good practice described in Bana et al. (2003, 2012): a lower reference level $v_j(\text{neutral}_j) = 0$, referred to as a data product with minimal satisfactory value (indicating neither a desirable nor undesirable performance), and an upper reference level $v_j(\text{good}_j) = 100$, referred to as a good data product. According to this model, the overall attractiveness of a decision alternative is derived as the weighted sum of the partial attractiveness v_{ij} , with weight w_j being a scaling constant (Dyer, 2005).

3.2. Problem structuring

The problem and context structuring phase consists of two key steps: identifying stakeholders and analyzing and understanding their objectives, as well as the decision problem (Franco & Montibeller, 2011).

3.2.1. Stakeholder identification at Galp energia

Identifying the stakeholders to be involved in model development at Galp is a key step for the success of the socio-technical approach. Hafner et al. (2024) proposed a reference ontology for data valuation as a business capability, identifying two key stakeholder roles required for this endeavor: data value determinators (DVDs), who act as decision-makers and operationally perform the data value assessment, and data value auditors (DVAs), who are specialists in data valuation.

Accordingly, in the present case, two teams were involved in model building: the data valuation team, which consisted of two DVAs from Instituto Superior Técnico Lisbon, who acted as facilitators and decision analysts along the modeling process, and two DVDs from Galp, who acted as the evaluators. The DVDs are part of Galp's data and analytics team in the renewable energy sector, holding the roles of *Team Lead, Advanced Analytics and Reporting*, and *Data Quality Manager*, ensuring they can accurately determine the value of data products within their domain. For a requisite approach in the Galp case study, two DVDs were deemed sufficient, as their combined perspectives on managerial, business, and technological operational aspects yield a comprehensive and robust assessment of the value of Galp's data products. Consequently, the setup is designed

such that the two DVDs act as evaluators, following the modeling steps, which range from formulating the decision problem to building a data product valuation model.

3.2.2. Objectives and decision problem framing

The data and analytics team of Galp's renewable energy sector delivers data-driven solutions, such as data products, to operational business units to a) support Galp's transformation into a data-driven enterprise and b) contribute to overarching enterprise objectives. These objectives include increasing topline growth and market share, optimizing processes and costs, fostering data-driven product innovation, and enabling fact-based decision-making.

Following the decomposition paradigm (Franco & Montibeller, 2011), these enterprise objectives are further detailed. Specifically, the sub-objective of increasing energy production directly supports Galp's topline performance. Furthermore, the objective of process and cost optimization encompasses improving operational efficiency, reducing time-to-market for data products, and increasing automation in data management processes. Additionally, the data and analytics team focuses on building efficient data pipelines to support the development of data products required by operational business units, thereby contributing to the overall objective of driving data-driven product innovation. Finally, fact-based decision-making in this context reflects the objective of developing data products based on quantified value estimates.

However, achieving these objectives presents Galp with three key problems: a) the backlog of data products proposed for development and implementation in the operational domains is extensive and exceeds the available development and implementation resources, b) this necessitates the prioritization of data products in a reliable, transparent, and reproducible manner, which is currently driven by gut feeling rather than evidence-based decision-making, and c) the criteria influencing these investment decisions are highly complex, encompassing business-, data-, and technology-related dimensions.

Thus, the expected outcome of applying a multi-criteria model is to evaluate and prioritize the data product backlog, informed by evidence and the views of Galp DVDs. This prioritization shall serve as a foundation for deriving consistent roadmaps for data product development and implementation.

3.3. Model structuring

In the model structuring phase, a value tree comprising objectives and criteria is constructed, criteria are operationalized through descriptors of performance, and decision alternatives, in this case data products, are identified (Bana et al., 2005; Franco & Montibeller, 2011).

3.3.1. Value tree, criteria, and descriptors of performance

Model structuring leads to the value tree depicted in Figure 2. The M-MACBETH software assists at different stages of model building, including the construction and visualization of a value tree composed of various nodes, which can be either criterion or non-criterion nodes. Criterion nodes are used to evaluate the partial attractiveness of data products, while non-criterion nodes serve to structure the value tree in alignment with stakeholder-specific needs (Bana et al., 2017). In the present case study, Galp explores the valuation of data products and the associated construction of a value tree from

an enterprise architecture perspective, following TOGAF (The Open Group, 2022).

The case for using TOGAF is as follows. The notion of value has already been addressed and modeled in several studies through the lens of enterprise architecture. For instance, Sales et al. (2019) have introduced a pattern language for modeling value in ArchiMate, thereby anchoring the concept of value within the domain of enterprise architecture research. This is achieved through value modeling in ArchiMate, a modeling language closely aligned with TOGAF. Sales et al. (2019) describe that the valuation of an object, such as a data product, is conducted by so-called value subjects (in the present case DVDs), who pursue distinct goals. A similar logic is followed by Aldea et al. (2015), who, in their metamodel, also connect stakeholders with the value they perceive based on the goals they aim to fulfill.

Beyond approaches focused on modeling value in the context of enterprise architecture, several studies also address the intersection of requirements engineering and enterprise architecture. According to Quartel et al. (2012), requirements engineering is inherently tied to the process of identifying solutions for specific problems, such as the valuation of data products. The authors further emphasize that requirements engineering is strongly intertwined with enterprise architecture, e.g. in the TOGAF context, enabling the transformation of identified and structured problems into holistic solution architectures.

Furthermore, the existing literature already documents early attempts to evaluate multiple criteria in enterprise architecture contexts. For example, Hannemann et al. (2022) developed a multi-dimensional model in the context of enterprise architecture following TOGAF, focusing on how digital transformation technologies influence EA principles. In addition, Zia et al. (2011) surveyed to examine the extent to which multi-dimensional approaches, specifically the AHP and the ANP, are applied in enterprise architecture, revealing that both are used to varying degrees.

Thus, although, based on the best of the authors' knowledge, no existing study has yet explicitly applied TOGAF to structure a value tree using the MACBETH approach, notable efforts have already been made to integrate value modeling, multi-criteria evaluation, and enterprise architectures. In light of these insights and the recommendation by Hafner et al. (2024) to embed data product valuation within a holistic enterprise architecture context, as already demonstrated in a separate case study with Galp, currently under peer review (Hafner et al., 2025), it appears appropriate to apply TOGAF to structure the value tree from the perspective of Galp's stakeholders.

The value tree in Figure 2 organizes the present research problem of Galp into three main areas of concern (corresponding to non-criterion nodes): business/process, data, and application/technology (see Section 4.1.2). These areas are further detailed into five dimensions (non-criterion nodes) that affect the development and implementation decisions for data products: operational efficiency, relevance to the business unit, effort, inbound data quality, and tool stack, all aligned with the objectives and defined by the DVDs during the workshops. At the bottom level of this value tree are seven evaluation criteria (criterion nodes) that follow the logic of the mathematical model (Equation 1).

After defining the value tree, particularly deriving the set of criteria required by the DVDs to determine the value of their data products, the operationalization of each criterion

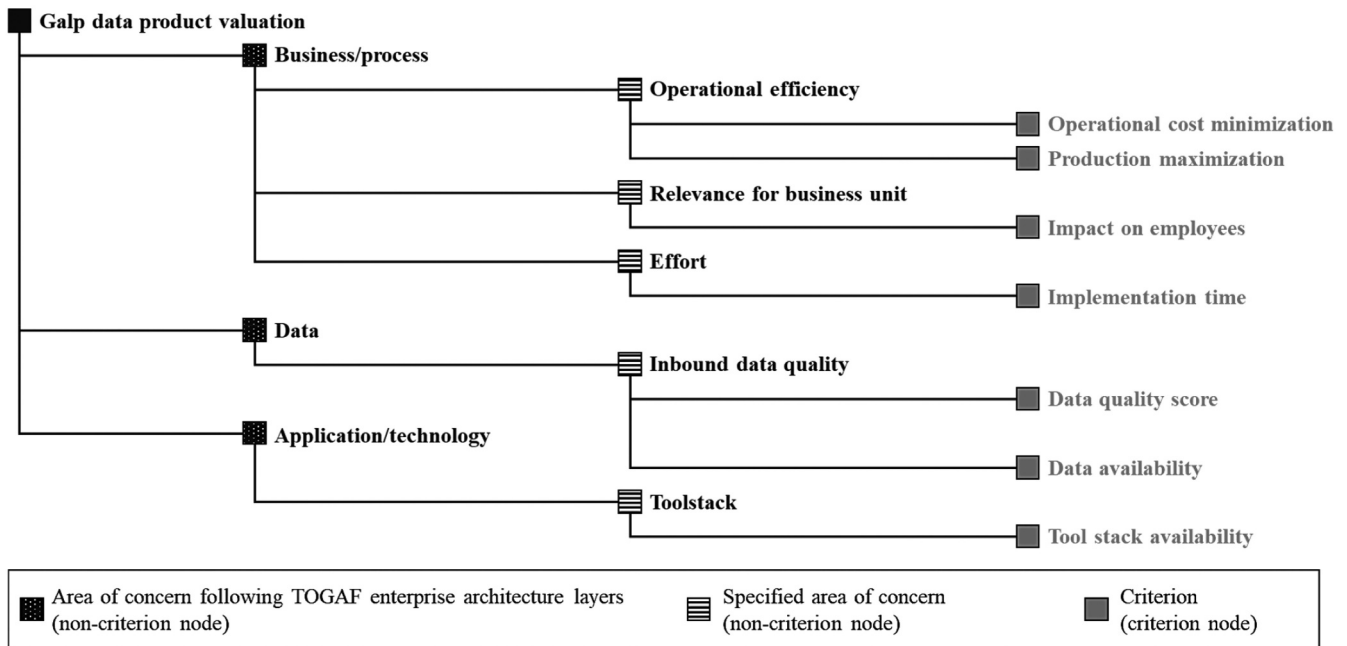


Figure 2. Value tree for data product valuation (built with M-MACBETH).

involves the construction of descriptors of performance, which are an ordered set of plausible performance levels that enable the measurement of the data product performances within each criterion (Bana et al., 2005). Most of the descriptors are of a qualitative nature, as found adequate by the DVDs, since there is a lack of information and data to assess data products quantitatively across most criteria. Despite this, the DVDs found these descriptors to be requisite for assessing performance across data products. As defined in equation (1), a performance level for a data product below the neutral level in a criterion has a negative (partial value) score, and is interpreted as an unsatisfactory level of performance on the data product. Conversely, a performance level above the neutral level and below the good level for the data product is regarded as having satisfactory performance (value score between 0 and 100); and a data product with performance above good has a very good or excellent performance, and a value score above 100. An overview of the criteria and detailed information on the descriptors of performance is provided in Table 1. The constructed descriptors were built to ensure that the model is reusable and can be used to assess new data products.

3.3.2. Data product alternatives and performances

The aim is to develop a model to evaluate data products, which requires defining the data products to be assessed. The DVDs defined and documented a set of data products, currently identified as potentially interesting by the data and analytics team of Galp's renewables business unit, in accordance with the data product definition outlined in Section 2.1. The set of data products is described in Table 2.

For each data product, performance was evaluated against each criterion (see Table 3).

Following equation (1), data products' performance in each criterion is converted into partial value scores, which are then rescaled by weighting coefficients to give an overall data product's value score. This score is to be interpreted as an interval scale (with anchors at the neutral and good

references, corresponding to 0 and 100, respectively, as described in equation (1)).

3.4. Building the multi-criteria data product valuation model

This section discusses the construction of value functions and weights, culminating in the model's testing, validation, and analysis of the results.

3.4.1. Value functions

To build value functions, the MACBETH qualitative pairwise comparison protocol of questioning is applied, in which Galp DVDs are asked to assess the differences in attractiveness between performance levels using the scale no difference, very weak, weak, moderate, strong, very strong, or extreme difference. Then, the M-MACBETH software (Bana et al., 2017) assists in converting qualitative judgments into compatible numerical value scales (using mathematical optimization programs) that can be discussed, adjusted, and validated by the DVDs. Qualitative pairwise comparisons and the constructed partial value scores for a selection of evaluation criteria are presented in Table 4. The additional qualitative pairwise comparisons and the constructed partial value scores are illustrated in the tables in the Appendix (Table A1 - Table A5). An example is provided here to enhance the clarity of the subsequent tables. In the criterion of data availability (see Table 4 having a qualitative descriptor of performance), the difference in attractiveness between the performance levels of *fully available* and *mostly available* is defined as *very strong*, whereas the difference between *fully available* and *hardly available* is considered *extreme* (the remaining judgments of the table should be interpreted accordingly). After discussion, Galp DVDs validated the cardinal value scales depicted on the right of Table 4.

The transformation of qualitative judgments into partial value scores was performed using the M-MACBETH software, with numerical scores being illustrated in Figure 3 for the qualitative performance descriptors. It is worth noting

Table 1. Overview of criteria and corresponding descriptors of performance.

Criteria (abbreviation)	Type of descriptor	Descriptor levels (reference levels)	Levels of performance description
Operational cost minimization (CostMin)	Qualitative, discrete	Massive impact	Cost minimization (time and/or material) for the entire solar and wind fleet
		High impact	Cost minimization (time and/or material) for a power plant cluster
		Marginal impact (good level)	Cost minimization (time and/or material) for singular power plants
		No impact (neutral level)	No cost minimization (neither time nor material) in the operational business
Production maximization (ProdMax)	Qualitative, discrete	Massive impact	Increased energy output for the entire solar and wind fleet
		High impact	Increased energy output for a power plant cluster
		Marginal impact (good level)	Increased energy output for a single power plant
		No impact (neutral level)	No measurable impact on the energy output increase
Impact on employees (ImpactEmpl)	Qualitative, discrete	Critical	Required either by legislation and/or top-management
		High (good level)	Constraining the smooth execution of business operations and/or is actively requested by the business
		Medium (neutral level)	Not affecting the smooth execution of business operations, but is actively requested by the business
		Low	Neither affecting the smooth execution of business operations nor actively requested by the business
Implementation time (ImplTime)	Quantitative, discrete	6 (good level)	6 months implementation time (development to operation)
		9 (neutral level) (expected to vary between 3 and 13)	9 months implementation time (development to operation)
Data quality score (DQScore)	Qualitative, discrete	High (good level)	Data is ready to use for data products with negligible data cleansing activities
		Medium (neutral level)	Data quality has certain weaknesses that can be addressed through data cleansing activities, enabling the data to be utilized for data products with a reasonable allocation of resources
		Poor	The data quality is so deficient that even additional data cleansing activities would require too many resources to make the data usable
Data availability (DatAvail)	Qualitative, discrete	Fully available	Inbound data is available and integrated via data stream/pipeline
		Mostly available (good level)	Inbound data is available, but is not integrated yet, though integration options exist
		Hardly available (neutral level)	Inbound data is partially available depending on the source, and in most cases, integrations are feasible
Tool stack availability (ToolAvail)	Qualitative, discrete	Not available	Inbound data is neither available nor integrated
		Fully available	From a developer perspective, the required tool stack (data pipelines, models, frontend) is approved, licensed, and ready to be applied
		Mostly available (good level)	From a developer perspective, the required tool stack (data pipelines, models, frontend), except max. one element, is ready to be applied, but workarounds may be implemented
		Hardly available (neutral level)	From a developer perspective, two or all elements from the required tool stack (data pipelines, models, frontend) are not ready to be applied, but potential resource-intensive workarounds may be implemented
		Not available	From a developer perspective, the required tool stack (data pipelines, models, frontend) is not available, and potential workarounds imply massive resource investments

Table 2. Data products (DP) for valuation.

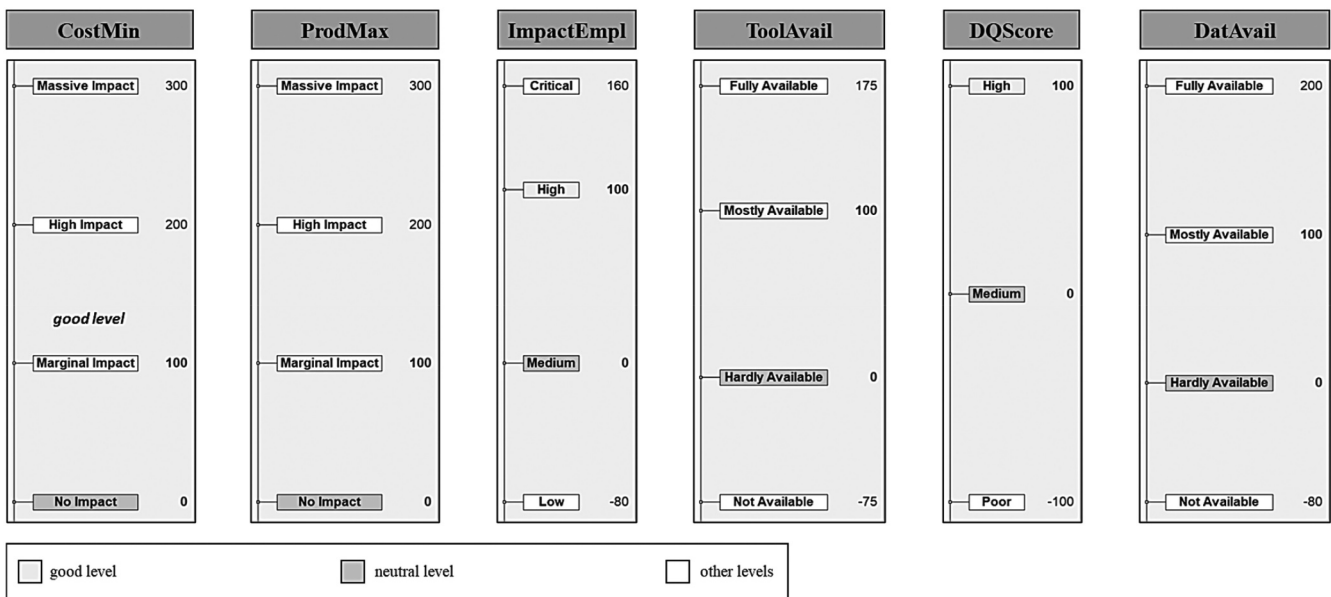
ID	Name	Description
DP1	Underperformance in string combiner boxes	An incident classification model in the combiner boxes enables control center operators to deploy operations and maintenance teams more rapidly and in alignment with the specific incident type, thereby supporting a safer, healthier, and more productive operation.
DP2	Predictive maintenance model for solar inverters	A failure risk prediction model for solar inverters can support higher production rates, as unprevented malfunctions in this equipment may affect the entire production of a solar power plant from days to months; such a model can advise control center operators to evaluate the performance of specific equipment and subsequently activate operations and maintenance teams to confirm the potential risk and act before failure occurs.
DP3	GenAI chatbot for operational data	An operational data query chatbot could be an important information resource for different teams at Galp, especially for supporting less data-technical profiles in analyzing and interpreting operational data.
DP4	Supply chain asset optimization with incident data	An incident-based supply chain optimization model that leverages each power plant's historical incident profile, accounting for incident frequency, severity, and other characteristics, enables the development of a more precise supply chain strategy for each asset, ultimately reducing operational costs by improving and targeting spare-part availability for maintenance.
DP5	Tracking control unit battery discharge prediction	A battery discharge prediction model can help improve production in individual solar power plants equipped with tracking control units (TCUs). The proper operation of the TCU enables the solar panels to maximize production through improved daily solar tracking. Since the TCUs are fed through solar energy, it is important to anticipate their movement capacity relative to weather forecasts and predicted solar production.

Table 3. Data products' table of performances.

Data product	CostMin	ProdMax	ImpactEmpl	ImplTime	DQScore	DatAvail	ToolAvail
DP1	No impact	High impact	High	9	Medium	Mostly available	Mostly available
DP2	High impact	Marginal impact	Medium	9	Poor	Mostly available	Mostly available
DP3	No impact	No impact	Medium	6	High	Fully available	Fully available
DP4	High impact	Marginal impact	Medium	6	Poor	Mostly available	Mostly available
DP5	Marginal impact	Marginal impact	Medium	6	Medium	Mostly available	Mostly available

Table 4. Qualitative pairwise comparisons and a validated partial value scale for the criterion data availability.

DatAvail	Fully available	Mostly available	Hardly available	Not available	Partial value scale
Fully available	No	Very strong	Extreme	Extreme	200
Mostly available	–	No	Very strong	Extreme	100
Hardly available	–	–	No	Strong	0
Not available	–	–	–	No	–80

**Figure 3.** Validated value scores for criteria with qualitative descriptors of performance.

that, to illustrate the applied methodology more effectively, the following visualization includes specific content from the case study. The results are described in detail in Section 4 and subsequently discussed.

For the criterion *implementation time*, which has a quantitative descriptor of performance, a continuous value function was constructed, with qualitative judgments depicted in Table 5 and the validated function shown in Figure 4.

During the partial value modeling process, if inconsistencies arise across qualitative pairwise comparisons, the M-MACBETH software identifies them and assists the facilitator and evaluators in resolving them. However, no inconsistent pairwise comparisons emerged during the modeling process. If there are differences in opinion between DVDs, they could discuss to reach a consensus, or more than one

MACBETH qualitative category can be used (this latter situation was not observed with Galp).

3.4.2. Criteria weighting

For building the criteria weights (i.e. scaling constants to convert the partial value into an overall value), MACBETH qualitative swing weighting (Bana et al., 2003, 2004, 2012) was implemented.

First, the DVDs were tasked with ranking the swings in decreasing order of relative importance, using questions such as: *Imagine there is one data product with neutral performances in all criteria. If the performance on one criterion could be improved from neutral to good, which criterion would the improvement be the most important?*

Second, the DVDs were asked to evaluate the contribution of each swing to the model following the questioning protocol:

Table 5. Qualitative pairwise comparisons and a validated partial value scale for the criterion implementation time.

ImplTime	3	6	9	12	13	Partial value scale
3	No	Weak	Strong	Very strong	Very Strong	166,67
6	–	No	Moderate	Strong	Very strong	100
9	–	–	No	Moderate	Strong	0
12	–	–	–	No	Moderate	–100
13	–	–	–	–	No	–200

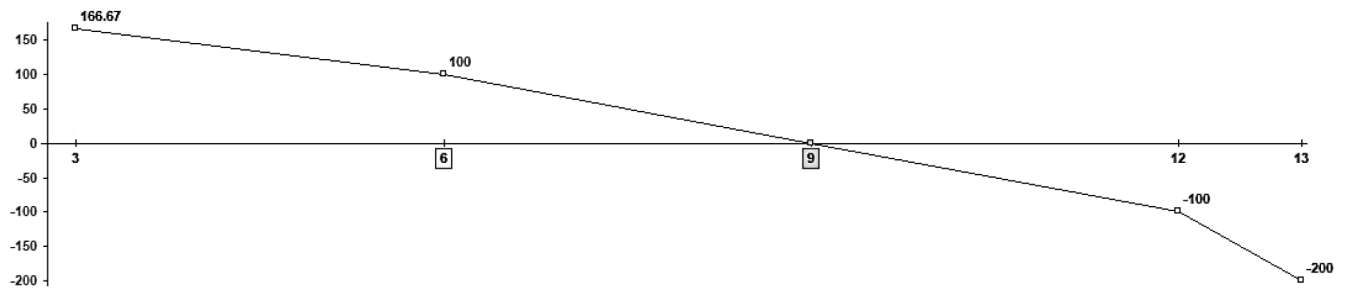


Figure 4. Validated value function for the criterion implementation time (from M-MACBETH).

Consider a data product that has neutral performance across all criteria; to what degree would an improvement from neutral to good in ‘impact on employees’ [ImpactEmpl] enhance the overall attractiveness of the data product (answer using the no, very weak, weak, moderate, strong, very strong and extreme difference scale)? This questioning process was systematically repeated for all swings, and the corresponding judgments were simultaneously entered into the last column of the M-MACBETH matrix of qualitative judgments portrayed in Table 6.

Third, qualitative judgments from the DVDs were elicited to assess the differences in attractiveness between swings. This was achieved by posing the following type of question: How much more attractive is a swing from neutral to good in ‘impact on employees’ [ImpactEmpl] compared to a swing in ‘operational cost minimization’ [CostMin]? This procedure was systematically applied to the other cells of the matrix of weighting judgments within the M-MACBETH software, which concurrently verified the consistency of the judgments and identified any inconsistencies requiring resolution. Table 6 presents the final matrix of weighted judgments after addressing and resolving some inconsistencies that arose during the process.

Based on qualitative judgments, the M-MACBETH software generated numerical weights, which could then be adjusted and validated. This process resulted in a histogram (see Figure 5) that was validated by the DVDs.

As illustrated in Figure 5, the DVDs assigned the highest relative importance to the criterion impact on employees, reflecting the service-oriented role of the data and analytics team in delivering data products required by the renewables business units. The weighting coefficient captures explicitly the size of the gap between medium and high impact on employees (i.e. the difference between neutral and good), and the extent to which the DVDs care about it. Comparatively, the DVDs were also deemed improvements from neutral to good in the criteria of operational cost minimization and production maximization, as they directly influence key enterprise objectives such as topline growth, market share expansion, and process and cost optimization. In contrast, improvements from neutral to good in the criteria data availability, tool stack availability, data quality score, and implementation time – closely tied to the feasibility of developing and implementing data products – were given lower relative importance. According to the DVDs, this

Table 6. Matrix with qualitative judgments.

	[ImpactEmpl]	[CostMin]	[ProdMax]	[DatAvail]	[ToolAvail]	[DQScore]	[ImplTime]	All neutral
[ImpactEmpl]	No	Strong	Strong	Strong	Very Strong	Very Strong	Extreme	Extreme
[CostMin]	–	No	Weak	Moderate	Strong	Strong	Very Strong	Very Strong
[ProdMax]	–	–	No	Moderate	Strong	Strong	Very Strong	Very Strong
[DatAvail]	–	–	–	No	Weak	Weak	Strong	Strong
[ToolAvail]	–	–	–	–	No	Weak	Moderate	Moderate
[DQScore]	–	–	–	–	–	No	Weak	Moderate
[ImplTime]	–	–	–	–	–	–	No	Weak
All neutral	–	–	–	–	–	–	–	No

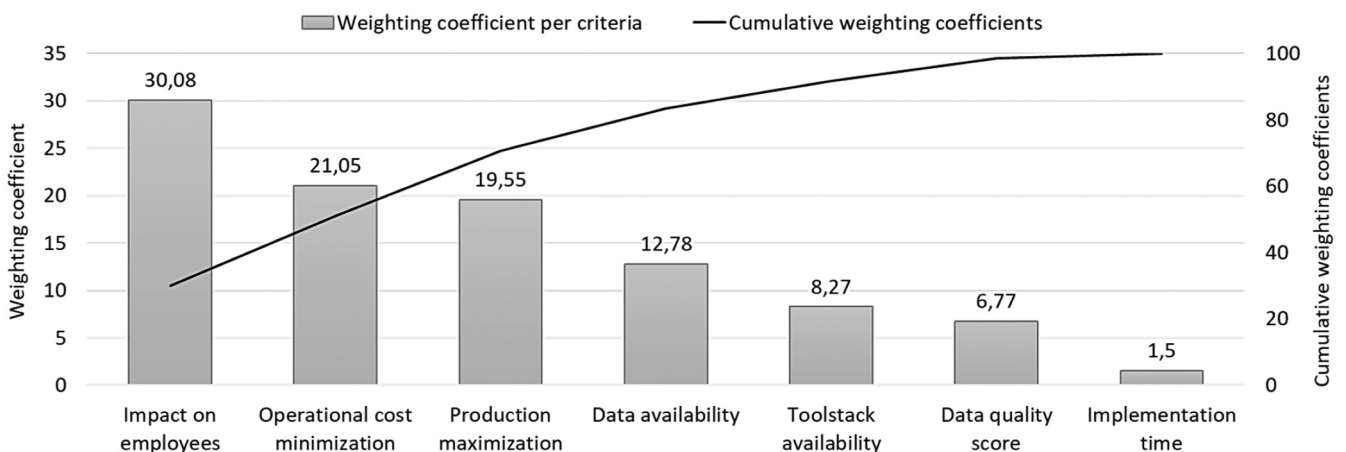


Figure 5. Weighting coefficients per criterion and cumulatively.

is partly explained by being criteria more directly influenced by the data and analytics team but with lower acceptance by the operational Galp renewables business units. The lower weight for implementation time reflected the argument that establishing impact for employees remains the primary objective for sustainable implementation of a data product, even in cases of increased implementation time.

3.4.3. Sensitivity and robustness analyses

In the final stage of model building, the data product valuation model was subject to sensitivity and robustness analysis, following scientific best practices, as mentioned, for example, in Bana et al. (2004), and Bana, Carnero, et al. (2012, 2017).

The sensitivity analysis in M-MACBETH facilitates the detection of recommendation variations when altering weighting coefficients while preserving proportionality among the remaining weights. By comprehending changes in the model's suggested data products with criterion weight adjustments, the DVDs gain insights into the dynamics of their model (Bana et al., 2001). In simpler terms, a sensitivity analysis explores how the output of an MCDA model changes when the inputs are altered, which helps validating the intuition and judgments of the DVDs to harden the overall MCDA model and its outcomes (Belton & Stewart, 2002).

Furthermore, during the information gathering process, there is inherent uncertainty, making it crucial to perform a robustness analysis to assess the strength of the findings. Moreover, a robustness analysis becomes important when modelling real-life situations with increasing complexity and imperfect knowledge, such as in the Galp case. Using M-MACBETH's robustness functionalities and considering the model as a whole, dominance and additive dominance can be explored within the robustness analysis. Dominance is defined as a situation where one data product outperforms another one in at least one criterion while performing equally well or better on all remaining criteria. Additive dominance (abbreviated as *Add. Dom.* in Table 8), in contrast, refers to a data product being consistently preferred over another when applying the specific additive model based on distinct levels of available information regarding value function judgments, weighting judgments, and constraints (Bana e Costa, De Corte and Vansnick, 2012; 2017).

4. Results

The overall value of the five data products under investigation can be determined by integrating all input parameters of the multi-criteria data product valuation model. According to Hafner and Mira da Silva (2023), the results of data valuation activities can be categorized into two distinct classes: a) the relative data value, which relatively compares the value of a data product to other data products, and b) the absolute data value, which aims to determine a specific or approximated value for a data product, such as in monetary terms, independent of other reference data products. In the case of the Galp data valuation model, the MACBETH approach is used to calculate the relative data product value, representing the overall performance of the five data products relative to one another and to data products with neutral and good performance (which serve as the weighting references adopted in Equation 1).

DP1 (under-performance string-box) has the highest value, with an overall score of 90.23. Consequently, DP1 demonstrates a significant gap in overall value compared to DP4 (supply chain optimization), which has an overall value of 77.43, and DP2 (predictive maintenance of solar inverters), with an overall value of 75.93. DP5 (TCU battery discharge prediction) has an overall value of 63.15, while DP3 (GenAI chatbot for operational data), with an overall value of 48.30, performs comparably poorly for the Galp DVDs. The overall results are visualized in Figure 6 and Table 7.

Looking at the results, it should, however, be noted that multi-criteria models in general, and the Galp data product valuation model specifically, may 'often involve imprecise data and uncertain information' (Bana e Costa, De Corte and Vansnick, 2012, p. 377). For this reason, it is recommended to conduct an in-depth discussion with the DVDs regarding the model, using sensitivity and robustness analyses, to test the model and, if necessary, adjust before model validation. Consequently, a sensitivity analysis was presented to the DVDs, examining the behavior of the model, especially the overall performance of DP1, when the weighting coefficients were altered while maintaining proportionality among the remaining weights (Bana e Costa 2001). The DP1 sensitivity analysis revealed two findings.

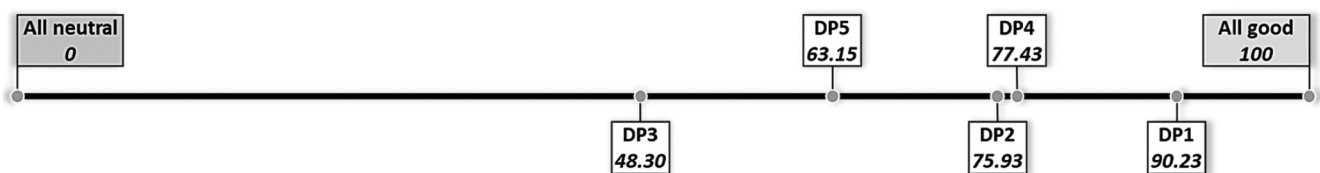


Figure 6. Overall value of data products.

Table 7. Matrix of partial and overall value (derived from M-MACBETH).

Options	Overall	CostMin	ProdMax	ImpactEmpl	ImplTime	DQScore	DatAvail	ToolAvail
DP1	90.23	0.00	200.00	100.00	0.00	0.00	100.00	100.00
DP2	75.93	200.00	100.00	0.00	0.00	-100.00	100.00	100.00
DP3	48.30	0.00	0.00	0.00	100.00	100.00	200.00	175.00
DP4	77.43	200.00	100.00	0.00	100.00	-100.00	100.00	100.00
DP5	63.15	100.00	100.00	0.00	100.00	0.00	100.00	100.00
All good	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
All neutral	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Weights		0.2105	0.1955	0.3008	0.0150	0.0677	0.1278	0.0827

Firstly, comparing the overall performance of the highest-performing data product (DP1) with that of the second-highest-performing data product (DP4) shows that altering the weighting coefficients for the criteria data quality score, data availability, and tool stack availability does not affect the prioritization order for data product development. Specifically, this means that despite modifications in these weighting coefficients, DP1 would consistently outperform DP4. In contrast, the highest sensitivity is observed in the weighting coefficient of the operational cost minimization criterion when it varies. More precisely, if the weighting coefficient is increased from 21.05 to 25.80, DP4 would surpass DP1 in overall value. A similar pattern can be observed across other criteria, although with significantly lower sensitivity. A reordering of the prioritization, where DP4 would outperform DP1, would hypothetically occur under the following conditions: a) production maximization weighting coefficient is reduced from 19.55 to 7.70, b) impact on employees weighting coefficient is decreased from 30.08 to 19.80, or c) implementation time weighting coefficient is increased from 1.50 to 12.70.

Secondly, based on the sensitivity analysis, there is also a potential scenario in which the lowest-performing data product, DP3, could outperform DP1 under specific adjustments to the weighting coefficients. Specifically, this would occur if the data quality score weighting coefficient was substantially increased from 6.77 to 34.30, the data availability weighting coefficient from 12.78 to 38.50, or the tool stack availability weighting coefficient from 8.27 to 41.20.

These adjustments in the weighting coefficients would represent significant changes to the evaluations by the DVDs. The DVDs discussed these results and did not consider it necessary to revise the model, as the measurements of the data products' performance were judged to be precise. The DVDs also considered that further sensitivity analysis was unnecessary and that the defined weighting coefficients were appropriate (as advised by Phillips and Bana e Costa (2007)).

Given potential imprecision in value functions and weights, conducting a robustness analysis was considered appropriate to assess the impact of variations in partial value scores on the model results. Therefore, the DVDs found it adequate to test a $\pm 5\%$ variation in the partial value scores and weights, assuming potential imprecision above and below the model parameters. Under this variation, dominance and additive dominance were observed in all data product comparisons. Even if the imprecision in value measurement increases from $\pm 5\%$ to $\pm 10\%$, corresponding to a doubling of the imprecision indicated by the DVDs, the additive dominance results remain consistently stable (see Table 8 for $\pm 5\%$ imprecision). This suggests that the model's conclusions remain robust despite minor variations in the

input data. Even when imprecision in value measurement is considered, results show that DP1 maintains the highest value among the options, and the ranking remains unchanged. Furthermore, it can be stated that DP4 consistently performed better or equally well across all criteria compared to DP2, and is therefore indicated as dominant in the table.

Based on the model results, including discussions of sensitivity and robustness analyses, the DVDs found the multi-criteria data product valuation model to be requisite for their intended purpose. Specifically, the model integrates relevant data products from the backlog, incorporates requisite criteria and their respective weighting coefficients, evaluates the value of each data product, and thus serves as a vehicle for effectively prioritizing data product development and allocating required resources to those data products.

Within the Galp context, this means that the data and analytics team of the Galp renewables division is prioritizing DP1 as the selected and first data product for development.

5. Discussion, implications, and future research

A discussion of both the findings from evaluating data products and the applied methodology is essential, together with implications, limitations, and avenues for future research.

5.1. Discussion on the generalizability of the model

Since the methodological focus of MACBETH is the development of a specific multi-criteria model for a dedicated case, in this section we discuss the extent to which the model is generalizable and transferable based on expert interviews to international experts from several countries conducted in a study in a related area (Hafner, Mira da Silva, et al., 2025).

In that study, 11 interviews were conducted with experts in data valuation and enterprise architecture management, with the objective to understand their views regarding the value of data in their contexts. The experts are based in Germany, the Netherlands, and Switzerland and work on a wide range of sectors, thereby extending the perspective of this case study, originally focused on a Portuguese company, to three additional countries and across sectors. Specifically, selected experts had in-depth knowledge of specific industries, such as automotive, manufacturing, or media, as well as on the consulting domain. This combination of experts provides an ideal complement to the multi-criteria data product valuation model developed in this study.

The following questions from the interviews were particularly relevant for this research:

Table 8. Robustness analysis of the multi-criteria data product valuation model with M-MACBETH, when a $\pm 5\%$ variation in the partial value scores and weights is considered.

	All good	DP1	DP4	DP2	DP5	DP3	All neutral
All good	=	Add. Dom.	Add. Dom.	Add. Dom.	Dominance	Add. Dom.	Dominance
DP1	-	=	Add. Dom.	Add. Dom.	Add. Dom.	Add. Dom.	Dominance
DP4	-	-	=	Dominance	Add. Dom.	Add. Dom.	Add. Dom.
DP2	-	-	-	=	Add. Dom.	Add. Dom.	Add. Dom.
DP5	-	-	-	-	=	Add. Dom.	Dominance
DP3	-	-	-	-	-	=	Dominance
All neutral	-	-	-	-	-	-	=

- (a) What are the main purposes of your enterprise when determining the value of your data?
- (b) What are the parameters affecting the value of data in your enterprise, and which of them would you consider the most relevant? c) Which tools, frameworks, and standards does your enterprise use to determine the value of data? The following paragraphs draw insights from the interviews (grounded in the transcribed interviews) in comparison with the findings of our study, in order to discuss the generalizability of the Galp model.

To begin with, it is important to note that the majority of interviewees across sectors emphasized that the value of data, for example, in the form of data products, strongly depends on the use case, the type of data, such as transactional versus master data, the data valuation context, and the individuals responsible for the valuation, namely, DVDs. All areas of concern, along with the corresponding criteria and performance descriptors, are derived from such context. This implies that a multi-criteria data product valuation model is not inherently generalizable or transferable across sectors, enterprises, or contexts, which supports the underlying MACBETH paradigm that a multi-criteria model must always be tailored to a specific context and decision problem (Franco & Montibeller, 2011; Bana e Costa, De Corte and Vansnick; 2012).

Nevertheless, the expert interviews reveal common concerns regarding what influences data value (similar to the areas of concern in Galp's model) and should therefore be considered in any data value assessment. However, the specification of criteria and of criteria's performance descriptors remain context-dependent and are influenced by each enterprise's level of maturity (Hafner, Mira da Silva, et al., 2025).

One particularly relevant area of concern identified across multiple sectors is data quality, which plays a central role in the automotive, manufacturing, financial services, media, government, and technology industries. Data quality can be broken down into several criteria. In the technology sector, particularly in the context of AI models, criteria such as model accuracy, F1 score, mean squared error, data availability, and data accessibility may be explored. The media sector places a stronger emphasis on data consistency and timeliness, for instance, in media usage analysis. In the governmental sector, completeness, accuracy, and latency are among the most critical criteria, similar to those in the automotive sector, which also include accessibility and availability, as highlighted by the interviewees. Therefore, data quality is expected to be a key concern in multi-criteria data product valuation models, regardless of the adopted criteria and exact measurement approach. In the present study, this was reflected through the inclusion of the criteria *data quality score* and *data availability*.

Another important area of concern across sectors is the consideration of business impact, often assessed through ROI perspectives. Typically, this involves considering two sides: the monetary benefit or the value-generating side and the cost or effort-related side. In the technology sector, for example, a relevant criterion on the benefit side is the conversion rate, which reflects how frequently a data-driven product is actually purchased. In the manufacturing sector, a benefit-related criterion is forecast accuracy in production processes, which can be improved by using appropriate data products. Other criteria frequently mentioned, particularly

by experts from the financial sector and those involved in sector-agnostic consulting projects, include topline improvements enabled by data, such as increased revenues. In the media sector, user engagement or retention is typically a central criterion on the benefit side, as discussed with the interviewees. In the present study on Galp, which operated in the energy sector, the benefit side is captured through the area of concern *operational efficiency*, specifically represented by the criteria *operational cost minimization* and *production maximization*. The second ROI-related side focuses on costs or required efforts. Experts from consulting, as well as from the automotive and technology sectors, emphasized the importance of evaluating the effort involved in providing and managing data (Hafner, Mira da Silva, et al., 2025). In the Galp case, this is reflected in the area of concern *effort* and by the criterion *implementation time*.

Another area of concern that emerged as particularly relevant across sectors in the interviews can be summarized as the data product's relevance to users. Experts from the technology, automotive, and consulting sectors emphasized that usage frequency and the resulting acceptance of data and related products are crucial. This is primarily influenced by the extent to which a data product addresses a specific requirement an individual faces. However, the perceived severity of such requirements can vary subjectively from person to person. In addition, the degree to which a data product is actually used depends on user skills and knowledge, that is their ability to interact with and benefit from the product in the first place. In the Galp case, this area of concern is addressed through the criterion *impact on employees* under the broader area of concern *relevance for business unit*.

In addition to these cross-sectoral areas of concern, the expert interviews also identified further aspects that may be relevant depending on the specific context. These include, for instance, the informational value, representativeness, and exclusivity of data. Another important aspect relates to regulatory requirements. Data products designed to fulfill regulatory obligations are often considered to have particularly high value (Hafner, Mira da Silva, et al., 2025). This aspect is especially significant in highly regulated sectors such as energy and government, or in enterprises operating within the scope of critical infrastructure.

In conclusion, while the developed multi-criteria data product valuation model is not directly transferable or generalizable to other sectors or enterprises, since data valuation must always be tailored to the specific context, the Galp model incorporates areas of concern and criteria relevant for distinct sectors. Future multi-criteria data product valuation models may therefore be guided by these cross-sectoral areas of concern and criteria, while refining and tailoring them to the specific context in which they are applied.

5.2. Content- and methodology-related discussion

In addition to the generalizability of the model, it is important to discuss the content and the underlying methodology, and to place it in the context of related research.

5.2.1. Theoretical and practical insights on the multi-criteria data product valuation model

Interpreting results within the literature, firstly, the assertion made by Brown and Escobar (2019, p. 4), that 'the data

products with the highest impact are those that are developed with knowledge of user requirements in mind' holds true for the Galp data valuation context. The involved DVDs at Galp further emphasized that the data and analytics team's role is not merely to provide data products for their own sake, but to address specific problems faced by data product consumers within the business units. This is particularly evident because the criterion *impact on employees* received the highest weight. Consequently, well-understood requirements (Quartel et al., 2012; Rahman, 2017) are crucial to capture and understand the needs of data product consumers systematically and to educate relevant stakeholders in the area of data products, their value, and their impact (Ramadan et al., 2024). These insights enable appropriate data products to be designed and implemented based on their value contribution.

Second, it is essential to involve stakeholders, particularly those with technical and business expertise, to effectively evaluate data products across diverse criteria. Members of the Galp data and analytics team have emerged as a robust best practice in this regard, as their proximity to operational business units and their technical capabilities have created appropriate conditions for determining the value of data products. In organizations with lower data maturity and potentially lacking organizational structures, conducting an in-depth stakeholder analysis to identify suitable participants may be crucial during the problem structuring phase (Franco & Montibeller, 2011). Given the multiple perspectives to be considered in a multi-criteria data product valuation model, a mix of DVDs with distinct technical and business skills is essential.

Third, a critical factor influencing the applicability and acceptance of a method like MACBETH, along with its associated software M-MACBETH, is the combination of high and intuitive usability with a theoretically sound model foundation (Bana e Costa, De Corte and Vansnick, 2012). MACBETH provides such a foundation and is recognized for its scientific relevance, as evidenced by its application across various domains and numerous successful studies (Bana e Costa, 2001; Phillips and Bana, DE Corte, et al., 2012; Ferreira & Santos, 2021; Phillips et al., 2007). However, stakeholders have indicated that the usability of the M-MACBETH software could be improved to more intuitively support decision-making in data product-related contexts, for instance, using other web-based platforms such as the one applied in the healthcare sector through the software *Wisdon* (Decision Eyes, 2019) or developing a specific software version for the data valuation context. Given the need to balance model complexity with resource investment, intuitively using a multi-criteria data valuation tool is key to minimizing administrative overhead in determining the value of data products while promoting agreement in evaluations.

Fourth, it becomes evident that determining the value of data products should not focus solely on a single primary criterion, whether technologically or business-driven. It is essential to avoid oversimplification, as various scholars have highlighted (Cong et al., 2022; Li et al., 2019), and instead, adopt a holistic perspective when evaluating data product value. This comprehensive approach can be achieved by considering the enterprise architecture layers of business, data, application, and technology, as specified by the TOGAF standard (Hafner et al., 2024). As demonstrated in the developed

Galp data product valuation model, each layer encompasses relevant criteria for assessing data product value. This holistic consideration is crucial for thoroughly prioritizing both the development and utilization of data products. However, it is essential to note that while increasing the diversity of criteria in the model can enhance the comprehensiveness of the results, the practical application requires careful consideration to balance model complexity. Regarding the diverse criteria, related research suggests that numerous additional factors may also be relevant for data valuation in other contexts, including costs (e.g. Cheong et al., 2023; Holst et al., 2020; Meierhofer et al., 2022; Pei, 2022; Stein et al., 2021; Tian et al., 2022), data security and privacy (e.g. Cabañas et al., 2017; Huang et al., 2020; Oh et al., 2020; Shen et al., 2022; Yu & Zhang, 2017), sentiment and perception, especially the willingness-to-pay of data product consumers (e.g. Bauer et al., 2012; Skatova et al., 2023; Zhang & Beltran, 2020), and information entropy (e.g. Li et al., 2017; Shen et al., 2019), among others. Considerations based on information entropy are particularly relevant in this context, as they build on the idea that data can reduce uncertainty (Liu et al., 2024; Mendizabal-Arrieta et al., 2023; Shen et al., 2019; Wang et al., 2021), an aspect that is especially critical in decision-making processes. In the specific case of resource allocation for the development of data products at Galp, reducing uncertainty through data is deemed central to ensuring effective, fact-driven decisions.

Fifth, the Galp data product valuation model findings indicate that data products that enhance Galp's business-critical processes hold the highest value, in contrast to those primarily supporting enablement processes, supporting the argument by Sales et al. (2018), that value and risk are deeply intertwined topics. Specifically, the incident classification model (DP1), the incident-based supply chain asset optimization model (DP4), and the failure risk prediction model (DP2) demonstrate relatively high overall data product value. These data products enable Galp to effectively manage and proactively mitigate incidents across its core operations, optimizing business-critical processes. Conversely, the operational data query chatbot (DP3) primarily impacts enablement processes rather than core business-critical incident management, resulting in a relatively low overall data product value. The battery discharge prediction model (DP5) further supports the hypothesis that data products that influence business-critical processes generate the highest value. While DP5 is not exclusively tied to enablement processes, it does not directly impact business-critical processes to the same extent as DP1 and DP4, which are directly related to incident management. Consequently, DP5 exhibits a significantly higher data product value than DP3. These observations suggest that structured requirements management should consider not only the domains in which data products are applied but also their modes of impact, distinguishing between enablement processes and core business-critical processes.

Sixth, based on the developed model and feedback from the DVDs, it becomes evident that multi-criteria approaches are robust for addressing complex decision-making problems in the field of information systems research. Previous studies, such as that by Pramanik et al. (2020), have already tackled the challenge of evaluating information systems projects using a variety of criteria and under conditions of uncertainty. Given that the decision to proceed with or against the development of a data product ultimately

manifests in a concrete development initiative or project, the proposed multi-criteria data product valuation model extends the work of Pramanik et al. (2020). It offers an alternative to the TOPSIS method, shifting the focus of information systems project evaluation toward data-product-centric projects. As a result, enterprises are provided with a practical tool underpinned by a theoretically sound foundation, enabling them to assess the value of data products more reliably, as proposed for future research by Li et al. (2019), and Cong et al. (2022). This, in turn, supports evidence-based, data-driven investment decisions and helps define the necessary framework conditions for successful realization.

Lastly, enterprises find themselves operating in a VUCA (volatile, uncertain, complex, ambiguous) world, shaped by various trends, rapidly changing internal and external factors, and a resulting dynamic that brings both opportunities and challenges for enterprises (Johansen & Euchner, 2013). Thus, one of the key challenges for leadership in enterprises 'is improving [their] ability to understand how [they] know what [they] know' (Johansen & Euchner, 2013, p. 12). It is therefore particularly relevant for leadership to ensure that decisions are made consciously and transparently. This enables organizations to trace the reasoning behind decisions (*how*), such as prioritizing data product developments based on estimated value, and to determine *which* actions to take, namely, which data product to implement. The proposed multi-criteria data product valuation model addresses both questions. It serves as a leadership instrument, supporting resilient and data-driven decision-making in VUCA environments while offering retrospective clarity. In doing so, it enables enterprises to understand why specific data product development decisions were made at a given time. This retrospective capability also opens up future potential, such as in the context of data value monitoring (Hafner et al., 2024), where the alignment between predicted and realized data product value can be assessed.

5.2.2. Comparison of related MCDA data valuation approaches

In addition to the broader discussion of this study's findings, this section compares the proposed MACBETH-based approach with the related approaches outlined in Section 2.2, highlighting the novelty, effectiveness, and practical advantages of this study. It is worth noting that no other study has employed MACBETH as the underlying methodology nor used alternative approaches framed within multi-attribute value theory, although certain similarities and differences can still be observed. First, within the specific context of data valuation, existing related work rarely demonstrates its approaches across diverse real-world environments. Even when applications beyond artificial examples are presented, they are typically limited to a single organizational setting or use case. The same applies to the model developed in this study. However, this limitation is reasonable, as data valuation is inherently context-specific and requires adaptation to the particular application scenario and organizational environment.

Another noteworthy distinction is that the present study deliberately relies on a single MCDA approach, which is adequate for the problem at hand. In contrast, other studies augment and combine additional methods, when their research contexts require such extensions (Alidrisi, 2021;

Bertoni, 2019; Si & Xiao, 2020). Although the combination of methods may be justified in some cases (Si & Xiao, 2020), such a combination was not necessary nor practical in our context. Each methodology may require dedicated expertise to guide stakeholders and apply the underlying tools and technologies. It is essential to note that value, in general, and data value, in particular, are strongly influenced by the subjective perceptions of the DVDs (Dole & Duxbury, 2024; Sales et al., 2018), and incorporating subjective dimensions – making use of a structured and transparent process – was key in the context of the Galp data product valuation model.

With regard to the underlying criteria, three related studies stand out by employing a particularly high number of criteria (18 criteria (Barham & Daim, 2020; Si & Xiao, 2020) and 19 criteria (Bertoni, 2019)). Other studies use considerably fewer criteria, namely three (Sachdeva et al., 2016), four (Pramanik et al., 2020), five (Alidrisi, 2021), or seven (Fleckenstein et al., 2023). The Galp data product valuation model uses seven criteria, indicating a reasonable level of detail and complexity, consistent with the need for balancing model simplicity and expressiveness (Cong et al., 2022; Si & Xiao, 2020; Sidgman & Crompton, 2016).

Related studies also show that reorganizing areas of concern is beneficial. The present Galp study follows a similar logic by structuring its areas of concern according to enterprise architecture layers based on the TOGAF framework. Other scholars, for example, Bertoni (2019), distinguish between customer and provider value; Barham and Daim (2020) organize their model into the four perspectives of people, technology, legal, and organization; and Si and Xiao (2020) organize their model into primary and corresponding secondary sets.

Differences also emerge in the type of questioning protocols used in model building. Several approaches utilize linguistic scales similar to those employed in the Galp case, albeit with varying levels of granularity. For instance, Sachdeva et al. (2016) introduce a 10-point linguistic scale for building weights, Alidrisi (2021) uses a 5-point scale, and Pramanik et al. (2020) adopt a 7-point scale. In comparison, the seven-level qualitative MACBETH scale offers a comparable degree of granularity, maintaining a balanced trade-off between complexity and simplicity. In contrast, Fleckenstein et al. (2023) propose a simplified scoring model with values ranging from 1 to 4. However, this overlooks whether the intervals between performance levels represent meaningful differences in attractiveness. MACBETH, by contrast, provides a bridge between ordinal and cardinal information, enabling a more accurate representation of differences in attractiveness, which provides a methodological advantage.

In summary, the MACBETH-based multi-criteria data product valuation model developed for Galp is well justified when compared to adjacent research. It enables building cardinal (numerical) scales with a friendly protocol of questioning, and the scientific robustness and practical applicability of MACBETH have been repeatedly demonstrated across various contexts (Ferreira & Santos, 2021).

5.3. Implications

The developed multi-criteria data product valuation model offers relevant implications for both academia and practice.

For real-world enterprises, four practical implications emerge: First, for tackling the challenge ‘that most companies still lack theoretical and practical tools for quantifying the value of the data in their ecosystem’ (Meierhofer et al., 2022, p. 10), the multi-criteria data product valuation model serves as a decision-support instrument for Galp to assess the value of its data products and to optimally allocate limited resources to their development. This enables the enterprise to maximize the overall value contribution of its data products.

Second, the model’s development fostered valuable discussions within Galp about current strengths and areas for improvement in data management. As such, the model not only supports the valuation of data products but also acts as a catalyst for identifying and debating broader optimization measures. This can help guide and coordinate data-related activities and, in the medium to long term, enhance Galp’s overall data maturity.

Third, a further practical implication concerns the mandatory compliance with regulatory and legal frameworks such as the EU-GDPR (European Parliament and Council of the European Union, 2016) and the EU AI Act (European Parliament and Council of the European Union, 2024). For example, under Article 37 of the EU-GDPR, a Data Protection Officer must be appointed if the data products involve extensive processing of personal data or systematic monitoring of data, including its emitters and consumers (European Parliament and Council of the European Union, 2016). This legal requirement highlights that data product valuation is not solely a technical endeavor but also necessitates an organizational change process (Hafner et al., 2024) to meet legal obligations. Furthermore, a key technological foundation of many Galp data products is AI, which has been regulated by the latest EU AI Act since 2024. The EU AI Act is legislation of the European Union that regulates the use of artificial intelligence based on a risk-oriented approach, to avoid hindering innovation while at the same time strictly controlling forbidden or high-risk AI applications (European Parliament and Council of the European Union, 2024). Consequently, the EU AI Act is particularly relevant for Galp and enterprises operating in a similar context to proactively manage data governance principles, documentation requirements, record-keeping obligations, and cybersecurity policies, among other measures, especially for data products ranked as highly critical, such as those related to critical infrastructure. Galp addresses this implication through its corporate data architecture, which serves as a foundational data layer for the entire organization and encompasses, among other elements, data governance, cybersecurity, and other legal compliance areas, such as the Data Protection Office. The various business units have designated data representatives who are responsible for adhering to this corporate data architecture, including maintaining detailed, continuously updated data governance descriptions, with particular attention to the EU-GDPR and the proper characterization of data products under the EU AI Act.

Fourth, the model demonstrates that even intangible assets, such as data products, can be evaluated in a structured, evidence-based manner rather than relying solely on gut feeling. By applying a scientifically grounded approach such as MACBETH to this context, DVDs at Galp, and potentially in other organizations, are empowered to make more robust and confident decisions.

Fifth, the conducted case study may serve as a source of inspiration for other organizations aiming to implement data product valuation using MCDA in general, and MACBETH in particular. While it is essential to acknowledge that the model was tailored explicitly to Galp and cannot be directly transferred to other contexts, the methodological approach, the applied criteria, and the structural foundations, such as those inspired by TOGAF, may provide valuable input for similar initiatives in other enterprises.

The present study also offers three important implications for academia. First, given that existing data valuation models are often criticized for being overly simplistic and inadequate in capturing the complexities of real-world challenges (Cong et al., 2022; Li et al., 2019), this research addresses that gap by introducing a multi-criteria data valuation model capable of dealing with the practical challenges inherent in assessing data value. In doing so, it helps narrow the divide between academic theory and real-world practice in the energy sector.

Second, to the best of the authors’ knowledge, while MACBETH has been applied in various contexts, such as faculty evaluation (Bana, DE Corte, et al., 2012, career choice problems (Bana et al., 2004), bid evaluation (Bana et al., 2008), and predictive maintenance auditing (Bana, Carnero, et al., 2012), it has not yet been employed within the field of data valuation. This study, therefore, extends MACBETH’s methodological reach into the domain of information systems.

Third, data valuation is a highly complex and inherently interdisciplinary research topic (Hafner & Mira da Silva, 2023), intersecting fields such as information systems (e.g. Attard & Brennan, 2018; Cong et al., 2022), finance, business, and management research (e.g. Brinch et al., 2021; Cheong et al., 2023; Veldkamp, 2023), and decision sciences (e.g. Li et al., 2019; Lim et al., 2024; Lin & Wu, 2016). This study contributes to building a shared conceptual and methodological foundation that can foster interdisciplinary dialogue and collaboration. By doing so, the study opens up promising avenues for joint research across these fields and encourages a more integrated approach to tackling data valuation challenges.

5.4. Limitations and avenues for future research

In addition to the implications, the study’s limitations and the resulting avenues for future research must also be acknowledged.

First, it should be noted that the case study focuses exclusively on Galp’s decision problem and the underlying model, including its criteria, is highly tailored to that context. While this level of customization is consistent with MACBETH’s intended use, it limits the model’s generalizability to other settings. This limitation is particularly evident in the use of strongly context-dependent criteria such as impact on employees. Accordingly, an avenue for future research lies in evaluating the extent to which the developed multi-criteria data product valuation model can be generalized to other enterprises and sectors, or whether it should rather be regarded as a source of inspiration and a structuring framework, which is the recommended use at this stage. Thus, following this research, it is worth developing a general framework, with a wide range of criteria as pointed out in academic literature (e.g. Lega et al., 2022), that can support future data valuation case studies in multiple contexts.

Second, within the scope of this case study, the value of the data products was determined by two DVDs from the data and analytics team. Expanding the group of involved DVDs, for example, by including stakeholders from non-technical business units, could support the validation and critical reflection of the results generated by the multi-criteria data product valuation model, thereby enhancing the accuracy, robustness, and acceptability of the outcomes. Consequently, a second avenue for future research lies in broadening the group of participating DVDs, provided that such an expansion is deemed cost-beneficial and relevant for Galp. For instance, the collaborative value modeling approach could be explored to engage a larger number of participants while promoting consensus (Vieira et al., 2020). At the time this study was conducted, however, such an extension was not considered justifiable.

Third, the cost-benefit considerations described above may lead to a general limitation of the multi-criteria data product valuation model. Developing and applying the model requires investment of organizational resources. Modern trends to boost efficiency, such as the use of artificial intelligence, were not incorporated in this study. However, AI offers a promising means to improve both the efficiency and robustness of the modeling process. Therefore, their exploration in the context of multi-criteria evaluation with MACBETH is proposed here as a future research direction.

Fourth, although the execution of the multi-criteria data product valuation model using MACBETH was seamless, with stakeholders showing a clear understanding of both the necessity and the functioning of the methodology, future studies may explore alternative weighting protocols. For instance, quantitative swing weighting as proposed by von Winterfeldt et al. (1986) could serve as a valuable alternative. Additionally, research could investigate user preferences for different elicitation and questioning protocols within the data product evaluation context to further improve stakeholder engagement and methodological fit.

Fifth, since the usability of supporting software for data product valuation was identified as a critical factor by the Galp DVDs. Thus, the development of a dedicated platform tailored to applying MACBETH in the data product context is recommended. Such a platform should aim to enhance user experience while maintaining methodological and scientific rigor.

Sixth, the present case study was conducted within a highly data-mature environment, specifically, in a company with a dedicated data and analytics team and many years of experience in data management. As a result, the study does not address how enterprises with lower data maturity might determine the value of their data. Thus, expanding the study to additional case studies could be beneficial. Future research could explore the adaptability of the developed model across sectors and organizations of varying sizes and information technology/data maturity levels. Particularly, the maturity level of information technology and data significantly influences an enterprise's capability to generate insights and drive improvements in overall performance (Peng et al., 2012). Therefore, it would be especially insightful to examine the impact of general information technology maturity and, more specifically, data-related maturity on data product valuation. Organizations may either tailor the model to their needs or establish prerequisites such as structured ideation, targeted

requirements management, or robust data governance. Broadening this study would refine the approach, enhance the model, and enable cross-sector comparisons to identify benchmarks and potential areas for improvement.

Seventh, value and risk are inherently interrelated concepts (Sales et al., 2018). While this case study has focused on the value perspective, the strong interdependence between both dimensions suggests that further research into the relationship between (data) value, data valuation, and risk management should be developed, as suggested by Tallon (2013), and Sales et al. (2018). It is therefore recommended that the investigation into how data valuation can be systematically linked to risk assessment and mitigation strategies be deepened.

Eighth, to facilitate the ideation of prospective data products within the context of data valuation, MCDA-related problem structuring methods, such as those proposed by Franco and Montibeller (2011), may be applied to design innovative data products that fuel the development of future data product valuation models.

7. Conclusion

Data is increasingly recognized not only as a fundamental asset but also as a commodity for enterprises across various sectors, including the energy industry. However, assessing the value of data products remains a critical challenge for both academia and industry, as their valuation is inherently complex, interdisciplinary, and contingent on the perspectives and requirements of their consumers. Consequently, many enterprises, if they evaluate the value of their data products at all, do so in an unstructured and non-transparent manner, often relying on expert judgment and gut feeling. To address this challenge, this study developed a multi-criteria data product valuation model to assist Galp, a leading Portuguese energy company, in analyzing which data products to pursue. This model was applied to assess the value of data products in Galp's renewables data product backlog, providing a robust foundation for prioritizing their implementation, in line with the need to generate value for the company and to improve resource allocation.

The developed multi-criteria data product valuation model, built upon the MACBETH multi-criteria approach for value measurement, evaluates five data products based on seven criteria aligned with the enterprise architecture layers: business, data, and application/technology. Specialists in data valuation and data value determinators from Galp collaborated in structuring the model, conducting assessments, and establishing a consensus-based data product valuation model. Notably, one data product (under-performance string-box) that directly impacts business-critical incident management processes was found to have the highest overall value relative to the others. As a result, this data product is now being pursued within Galp's development activities.

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ORCID

Markus Hafner  <http://orcid.org/0000-0001-5543-6010>
 Miguel Mira da Silva  <http://orcid.org/0000-0002-0489-4465>
 Mónica D. Oliveira  <http://orcid.org/0000-0003-4053-9214>
 Henderik Alex Proper  <http://orcid.org/0000-0002-7318-2496>

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Appendix

Table A1. Qualitative pairwise comparisons and validated partial value scale for the criterion operational cost minimization.

CostMin	Massive impact	High impact	Marginal impact	No impact	Partial value scale
Massive impact	No	Strong	Very strong	Extreme	300
High impact	–	No	Strong	Very strong	200
Marginal impact	–	–	No	Strong	100
No impact	–	–	–	No	0

Table A2. Qualitative pairwise comparisons and validated partial value scale for the criterion production maximization.

ProdMax	Massive impact	High impact	Marginal impact	No impact	Partial value scale
Massive impact	No	Strong	Very strong	Extreme	300
High impact	–	No	Strong	Very strong	200
Marginal impact	–	–	No	Strong	100
No impact	–	–	–	No	0

Table A3. Qualitative pairwise comparisons and validated partial value scale for the criterion impact on employees.

ImpactEmpl	Critical	High	Medium	Low	Partial value scale
Critical	No	Moderate	Very strong	Extreme	160
High	–	No	Very strong	Extreme	100
Medium	–	–	No	Strong	0
Low	–	–	–	No	–80

Table A4. Qualitative pairwise comparisons and validated partial value scale for the criterion data quality score.

DQScore	High	Medium	Poor	Partial value scale
High	No	Very strong	Extreme	100
Medium	–	No	Very strong	0
Poor	–	–	No	–100

Table A5. Qualitative pairwise comparisons and validated partial value scale for the criterion tool stack availability.

ToolAvail	Fully available	Mostly available	Hardly available	Not available	Partial value scale
Fully available	No	Moderate	Very strong	Extreme	175
Mostly available	–	No	Strong	Very strong	100
Hardly available	–	n/a	No	Moderate	0
Not available	–	–	–	No	–75

Table A6. Summary table data product valuation modeling process.

Step	Activity	Applied methodologies, frameworks, models, and tools	Involved stakeholders	Outcomes
Problem structuring	Stakeholder identification at Galp Energia	<ul style="list-style-type: none"> Stakeholder role setup following the reference ontology for a data valuation business capability (Hafer et al., 2024) Stakeholder identification and mapping (Franco & Montibeller, 2011) 	<ul style="list-style-type: none"> DVDs (execution) DVAs (facilitation) 	<ul style="list-style-type: none"> Stakeholder map Responsibilities in the process
	Objectives and decision problem framing	<ul style="list-style-type: none"> Problem decomposition (Franco & Montibeller, 2011) MACBETH (Bana e Costa, De Corte and Vansnick, 2012) 	<ul style="list-style-type: none"> DVDs (execution) DVAs (facilitation) 	<ul style="list-style-type: none"> Case study problem Refined research question
Model structuring	Value tree, criteria, and descriptors of performance	<ul style="list-style-type: none"> Value tree creation with the Criteria and descriptor of performance definition following MACBETH (Bana e Costa, Costa and Beinat, 2005) TOGAF (The Open Group, 2022) 	<ul style="list-style-type: none"> DVDs (execution) DVAs (facilitation) 	<ul style="list-style-type: none"> Structured value tree Criteria Descriptors of performance (qualitative and quantitative) Performance and reference levels including explanation
	Data product alternatives and performances	<ul style="list-style-type: none"> Decision option (data product) definition following MACBETH (Bana e Costa, De Corte and Vansnick, 2012) 	<ul style="list-style-type: none"> DVDs (execution) DVAs (facilitation) 	<ul style="list-style-type: none"> Data products including descriptions Performances of data products per criteria
	Value functions	<ul style="list-style-type: none"> Executing qualitative pairwise comparisons of performance levels per criteria following MACBETH (Bana e Costa, De Corte and Vansnick, 2012) M-MACBETH software (Bana e Costa, De Corte and Vansnick, 2017) 	<ul style="list-style-type: none"> DVDs (execution) DVAs (facilitation) 	<ul style="list-style-type: none"> Partial value scales Value functions
Model analysis	Criteria weighting	<ul style="list-style-type: none"> Executing MACBETH qualitative swing weighting and deriving weighting coefficients (Bana et al., 2003, 2012; Bana e Costa and Chagas, 2004) M-MACBETH software (Bana e Costa, De Corte and Vansnick, 2017) 	<ul style="list-style-type: none"> DVDs (execution) DVAs (facilitation) 	<ul style="list-style-type: none"> Qualitative judgement matrix Weighting coefficients (per criteria and cumulative)
	Result formulation and discussion	<ul style="list-style-type: none"> Sensitivity analysis (Bana e Costa, 2001) Robustness analysis (Bana e Costa, De Corte and Vansnick, 2012, 2017) M-MACBETH software (Bana e Costa, De Corte and Vansnick, 2017) Discussion of results, implications, limitations, and avenues for future research considering academic literature 	<ul style="list-style-type: none"> DVDs (discussion) DVAs (execution) 	<ul style="list-style-type: none"> Overall value of data products Matrix of partial and overall value Insights in model robustness and sensitivity Implications, limitations, and avenues for future research