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Measuring value-based management using natural language processing

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ABSTRACT

We propose an alternative approach to quantifying a firm's value-based management (VBM) sophistication. The approach uses natural language processing (NLP) and builds on a newly developed, customised dictionary. We describe the development of this dictionary and validate the resulting measure for a large sample of European listed firms (STOXX Europe 600 Index) using tests of internal consistency, construct validity, and relevant robustness checks. In doing so, we present a novel application of NLP in management accounting. We also contribute a customised, open-source dictionary for the measurement of VBM sophistication thereby creating opportunities for future research.

1. Introduction

Value-based management (VBM) is an integrated management approach that seeks to maximise long-term value creation (Jensen, 2002; Koller et al., 2020). Historically, it has been a challenge to develop valid and reliable measures for VBM (Wobst et al., 2025), and studies that measure VBM have often relied on surveys (e.g., Burkert and Lueg, 2013; Nowotny et al., 2022) or manual content analyses (e.g., Firk et al., 2021; Firk et al., 2019c; Firk et al., 2016; Knauer et al., 2018; Mavropulo et al., 2021). Both approaches are resource intensive as they require pre-testing and gathering survey data or manually coding and corroborating content analysis data (Bae et al., 2023; Qiu et al., 2023). Firk et al. (2021) and Wobst et al. (2025) suggest complementing existing approaches to measuring VBM implementation by using textual analysis, that is, natural language processing (NLP) methods, to automatically extract information from text data (Bochkay et al., 2022).

NLP methods for measuring VBM offer a promising alternative to surveys and manual content analyses for several reasons. First, the limitations of existing VBM measurement methods make a text-based approach especially valuable, as traditional methods (surveys; manual content analysis) are resource-intensive and lack scalability (Behlau et al., 2023; Firk et al., 2021; Ranta et al., 2023; Short et al., 2010). Second, the textual nature of VBM further justifies a customised dictionary: VBM is deeply embedded in the language of corporate reporting, and can therefore be systematically analysed for patterns of adoption and sophistication (Burkert and Lueg, 2013; Loughran and McDonald, 2016; Neuendorf, 2016). Third, beyond methodological novelty, our conceptually grounded study offers a scalable measure of VBM sophistication. Fourth, an extensive measure such as ours enables granular comparisons of VBM-related discourse across firms and industries, capturing variation in its prevalence and dimensional coverage (Firk et al., 2016; Wobst et al., 2025). Fifth, the potential for longitudinal and cross-cultural comparisons underscores the utility of such a measure, as it can track the evolution of VBM practices over time and examine how economic, cultural, and institutional factors shape their adoption globally (Burkert and Lueg, 2013; Fiss and Zajac, 2006; Meyer and Höllerer, 2010). Sixth, an open-source tool bridges theory and practice by helping companies to align their VBM practices with industry standards and optimise their VBM strategies (Boyd et al., 2022; Ittner et al., 2003; Lewis and Young, 2019; O'Kane et al., 2021). We

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acknowledge that such tools could be misused for symbolic purposes (for VBM, we coin the term *goldwashing*). Yet, research suggests that the influence of academic accounting insights on practice remains limited (Federsel et al., 2024; Tucker and Schaltegger, 2016).

However, no study has yet applied NLP methods to the measurement of VBM. In general, NLP applications are in their infancy in management accounting (Ranta et al., 2023). One example is that of Qiu et al. (2023), who employ textual machine learning to explore the breadth of management accounting practices as a package, using annual reports as their data source. They rely on a *dictionary approach* which counts the occurrence of words or *n-grams* (specific combinations of words) in texts (Loughran and McDonald, 2016): such dictionaries contain the n-grams that represent the underlying phenomena (Short et al., 2010). This approach is applicable across the most common data sources in accounting research, including annual reports, internal reports (e.g., on quality, sustainability, or compliance), meeting notes, conference calls, public news, public speeches, social media accounts, and interviews (Bochkay et al., 2022; Lewis and Young, 2019; Mahlendorf et al., 2023; Neuendorf, 2016; O'Kane et al., 2021; Short et al., 2018).

Responding to recent calls by Firk et al. (2021) and Wobst et al. (2025), the *purpose of this study* is to develop and validate a customised dictionary that measures VBM sophistication and to provide a detailed guide that describes how to apply NLP in this management accounting setting. We define VBM sophistication as the extent to which a firm embeds all necessary VBM practices (Burkert and Lueg, 2013; Firk et al., 2019c; Wobst et al., 2025), such as value-oriented portfolio management, target setting, operational integration, compensation linking, and fostering a value-based culture. To construct the VBM sophistication measure, we used a five-step process: (1) starting with a deductive approach to identify key VBM seed words from theory and literature, (2) expanding these using an inductive analysis of corporate reports to find related terms, and (3) refining them into n-grams for contextual precision. The dictionary was (4) validated through keyword-in-context analysis and a structured review by independent researchers with domain knowledge, and (5) final adjustments were made to include inflections and standardise variations. This resulted in a robust dictionary of 419 n-grams representing core VBM dimensions. We analysed 2500 firm-year observations from 2010 to 2018, focusing on non-financial firms listed in the STOXX® Europe 600 Index. We used annual reports as the primary data source and supplemented our analyses with financial and market data from Refinitiv Eikon and Datastream. Our findings demonstrate that the text-based VBM sophistication measure effectively captures firms' use of VBM language. The most frequently used n-gram in absolute terms ($n = 8807$), *value creation*, appears in 67 % of annual reports, alongside terms such as *shareholder return(s)* (58 %) and *cost of capital* (78 %). Our measure demonstrates robust internal consistency and construct validity, with a significant Spearman's correlation of 0.54 ($p < 0.01$) to the manually coded VBM benchmarks established by Firk et al. (2019c). Discrepancies between these two measures emerge at higher levels, likely due to differences in granularity: our NLP-based measure captures nuanced linguistic variations, whereas the manual measure assesses broader organisational integration. Further analysis reveals that our measure of VBM sophistication is associated with accounting performance, and aligns with established drivers such as capital intensity. It also provides granular insights: significant variation in VBM sophistication is evident across industries, with utilities scoring the highest and healthcare the lowest. Across countries, Austria and Germany exhibit high VBM sophistication, whereas others show significant variability (for instance, Portugal). These findings underscore the importance of institutional environments in shaping management practices. Overall, VBM sophistication has steadily increased over time. VBM practices exhibit limited year-to-year variation within firms compared to differences between firms, reflecting long-term strategic commitments.

This study contributes to the literature in several ways. First, it contributes methodologically to VBM research by providing an open-source, customised dictionary for future studies, which can be used as an alternative approach to existing methods for measuring VBM sophistication (Burkert and Lueg, 2013; Firk et al., 2021; Mavropulo et al., 2021; Nowotny et al., 2022), responding to existing research calls (Firk et al., 2021; Wobst et al., 2025). Second, we illustrate how to develop such a computerised measure and assess its validity. Our descriptions may serve as a foundation for future studies that wish to create and validate dictionaries in their own areas of interest. Third, following Qiu et al. (2023), we expand their seminal, China-based study on management accounting and NLP-based methodology in two ways: we enhance their existing evidence by applying NLP to an international setting as well as responding to their call for validated NLP-based results by testing for capital market performance.

2. Background: defining and measuring VBM sophistication

This section defines VBM, presents the corresponding definition of VBM sophistication, and outlines approaches for measuring both.

2.1. Definition of VBM

VBM first emerged under the term *shareholder value (maximisation)* as part of the Anglo-American governance model in the 1970s and 1980s (Meyer and Höllerer, 2010; Rappaport, 1981). Its core principle is that firms create value if they earn returns above their cost of capital (Bromwich and Walker, 1998; Koller et al., 2020; Rappaport, 1981). In academia, this concept became recognised as VBM, a management practice closely tied to managerial accounting and governance (Fiss and Zajac, 2004; Ittner and Larcker, 2001). VBM incentivises managers to implement projects that create value by establishing value-based metrics that connect the firm's key value drivers with a set of performance measures (Burkert and Lueg, 2013; Firk et al., 2016; Koller et al., 2020). VBM is a forward-looking concept that encompasses all present and future profits a firm creates for its shareholders (Edmans, 2021; Jensen, 2002; Koller et al., 2020); thus, firms with diligent VBM practices in place will undertake actions in line with the long-term interests of their value-relevant stakeholders (Edmans, 2021; Porter and Kramer, 2011).

Following the systematic literature review by Wobst et al. (2025), the prevailing definitions of *VBM sophistication* across the literature are grounded in Burkert and Lueg (2013) and Firk et al. (2019c). See Appendix A for a discussion of the term's development in the literature. Therefore, we build our definitions on these two initial VBM studies. Burkert and Lueg (2013, p. 5) define VBM as follows:

> *"VBM supports decision making directed toward the objective of shareholder value creation. Emanating from a superordinate key financial figure, VBM links the company's strategic objectives to a coherent set of performance measures through cause-and-effect-chains ('value drivers') that include all relevant processes and all pertinent information systems across a company. This information forms the basis for setting targets and determining action plans for employees."*

Firk et al. (2019c, p. 419) define VBM as follows:

> *"VBM aims to align organizational decision making with value creation by integrating different elements into the management system that allow for better control of value creation."*

While these definitions show minimal differences, their measurements differ slightly. Firk et al. (2019c) measure five VBM sub-constructs in a binary manner[3]: they exclude the evaluation of action plans for employees and the cultivation of a value-based culture, instead extending the measurement of VBM by explicitly examining its linkage to compensation. Burkert and Lueg (2013) measure VBM with six sub-constructs on a Likert scale from 1 to 7, using a survey involving top executives,[4] and, although they base their VBM definition on sources that emphasise the critical role of compensation (Biddle et al., 1997; Fiss and Zajac, 2004; Ittner et al., 2003; Malmi and Ikäheimo, 2003), they only imply that target setting and a value-oriented mindset ultimately serve the decision-influencing role (compensation) of VBM. Firk et al. (2019c), however, make this assumption explicit. Synthesising the discussions on conceptualising VBM (Burkert and Lueg, 2013; Firk et al., 2019c; Wobst et al., 2025) and corporate purpose (Edmans, 2021; Jensen, 2002; Porter and Kramer, 2011), we update their definitions of VBM (-practices) as follows:

> *VBM aligns the managerial decision-making (decision facilitating) and control (decision influencing) of all organisational objectives with the corporate purpose of long-term, enlightened value maximisation for its shareholders and value-relevant stakeholders. VBM encompasses interconnected components, including (1) value-oriented portfolio management, which directs strategic choices based on value maximisation and quantifies this through a core financial metric. VBM extends to (2) target setting, which establishes benchmarks rooted in value-creation objectives. VBM exhibits (3) operational integration, which incorporates both financial and non-financial value drivers. This integration is achieved through comprehensive procedural descriptions, such as action plans, that guide value-driving processes at all levels. Additionally, VBM includes (4) compensation linking, where rewards are tied to the achievement of value-based metrics. VBM fosters a (5) value-based culture that cultivates a mindset that prioritises shareholders.*

2.2. Definition of VBM sophistication

After defining VBM, Burkert and Lueg (2013) and Firk et al. (2019c) consistently define VBM sophistication as:

> *"[… the extent to which the practice is implemented within a company." (*Burkert and Lueg, 2013*, p. 5); and,*
>
> *"[… the extent to which an organization's actual implementation of VBM incorporates elements of the generalized normative framework." (*Firk et al., 2019c*, p. 426)*

Wobst et al. (2025, p. 8 & 11) are first to problematise in their literature review that some studies interpret VBM sophistication (the *extent*) only as the hierarchical permeation (the *depth*) of the VBM sophistication, while others – despite using the same definition – translate VBM sophistication (which they also often refer to as the *extent*) into measuring the number of practices employed (the *breadth*) at selected hierarchical levels only (e.g., Bluhm and Martens, 2009; Brück et al., 2018; Fiss and Zajac, 2004). This difference did not spark debate in the original studies of Burkert and Lueg (2013) and Firk et al. (2019c), since both measure the depth of implementation across a (slightly different) broad set of practices. Our synthesised and updated (Wobst et al., 2025) definition explicitly incorporates both *breadth* and *depth*:

VBM sophistication is the extent (depth) to which a firm embeds necessary (breadth) VBM practices.[5]

2.3. Measurement of VBM(-sophistication)

Methodologically, the literature has relied on several approaches to measuring VBM and VBM sophistication (Wobst et al., 2025). Most scholars have used surveys (e.g., Burkert and Lueg, 2013; Dekker et al., 2012; Ittner et al., 2003; Nowotny et al., 2022; Ryan and Trahan, 2007) or manual content analyses to quantify VBM adoption or sophistication from annual reports (e.g., Brück et al., 2023; Firk et al., 2019c; Firk et al., 2016; Fiss and Zajac, 2004; Knauer et al., 2018). Such fine-grained measures reflect that practices can be more or less sophisticated, leading to the detection of differences in VBM sophistication across adopters (Burkert and Lueg, 2013). While these studies tend to assert theoretical alignment with prior literature, their definitions and measures often reveal nuanced differences. For example, Firk et al. (2019c) extend the work of Burkert and Lueg (2013): they use annual reports to measure compensation but omit, for instance, VBM culture. Slight differences in this field are, therefore, accepted due to the idiosyncrasies of methods and datasets. Our study complements existing approaches to measuring VBM sophistication by employing NLP.[6] It further aligns management accounting research with advances in related fields such as financial accounting, finance, and organisational studies. Please see Appendix B for an overview.

3. Development of the text-based VBM measure

3.1. Choice of sample frame and text data selection

We derive our sample from the STOXX Europe 600 Index, which covers nearly 90 % of the total market capitalisation of the investable European market, and includes firms from 17 European countries. The European context is a suitable setting to study VBM because of its widespread usage in European firms (Firk et al., 2019c; Nowotny et al., 2022). Adoption and non-adoption of VBM is equally legitimate in Europe which enables the study of *differences* in VBM (Etzion, 2014; Meyer and Höllerer, 2010). Although our dictionary is based on European annual reports, the underlying VBM terminology reflects a globally diffused discourse. Fiss and Zajac (2004) suggested that the U.S.-origin concept of VBM is expressed in semantically consistent terms, with only its adoption differing across institutional contexts. Meyer and Höllerer (2010) support the view that VBM terminology is conceptually stable, while institutional logics merely alter their framing. Burkert and Lueg (2013, p. 7) even propose the existence of a "*VBM-pertinent*

[3] The sub-constructs are: 1) value orientation: commitment of a firm to the overall objective of value creation; 2) value-based metric adoption: adoption of a value-based metric (e.g., economic value added) as the key financial performance indicator; 3) target setting: setting targets based on the adopted value-based metric; 4) compensation linking: linking compensation to the adopted value-based metric; 5) operational integration: integrating the adopted value-based metric into lower levels of the organisation (e.g., markets, divisions, or business units).

[4] The sub-constructs are: 1) portfolio strategy (selection among alternative strategies based on expected value addition); 2) financial value drivers (integration of generic financial drivers to guide strategic decisions); 3) non-financial value drivers (use of relevant, firm-specific, non-financial indicators); 4) action plans (development of actionable plans based on key performance indicators (KPIs)); 5) target setting (setting of targets focused on long-term value and synergy); 6) value-based mindset (cultivating a mindset focused on shareholder value across the organisation).

[5] The necessary set of VBM practices is specific to each firm, for example, its structure, industry membership, or regulatory context. For instance, the use of stock options in compensation is emblematic of VBM, but cannot be implemented by unlisted, yet value-based, firms.

[6] Different NLP methods exist to generate text measures. Examples include rule-based methods such as dictionary-based approaches, and machine learning approaches such as topic modelling, text regressions, and decision trees (Bochkay et al., 2022). The choice of an NLP method depends on factors such as functionality and simplicity (Bae et al., 2023; Bochkay et al., 2022). Prior research indicates that dictionary-based approaches can be as powerful as other machine learning approaches such as Naïve Bayes (Henry and Leone, 2016). Scholars advocate the choice of simple methods because they are easy to understand and provide economically meaningful interpretations (Bae et al., 2023; Henry and Leone, 2016).

language" and see no need for contextualisation. The recent systematic literature review by Wobst et al. (2025) implies that VBM terminology is conceptually consistent across their international research samples, as they report no findings on localised terminology.

To avoid survivorship bias, we selected non-financial firms that were listed in the index at the beginning of our research period in 2010 and continued to track these firms until the end of our study period in 2018. Firm-year observations where firms ceased to exist due to insolvency were marked as having missing data and were excluded from further analysis. We manually collected annual reports from the investor relations sections of firms' websites[7] for use as text data and obtained financial data from the Refinitiv Eikon and Datastream databases to validate our text-based measure. Annual reports are suitable for measuring VBM because they are reviewed by an independent auditor, which should make them a reliable source of the firm's actual financial and strategic situation (Firk et al., 2016). Corporate annual reporting packages vary due to heterogeneous disclosure requirements across countries and firms' discretion in designing reports. To ensure comparability and consistency, we collected only those reports that met the following *ex ante* defined criteria: (1) available in English; (2) contain information about management, governance, and remuneration[8]; and, (3) cover a complete fiscal year. Moreover, we included only firm-year observations available for regression analysis and free from data constraints (e.g., missing or negative sales values). The final sample consisted of 2500 firm-year observations. Table 1 summarises the sample selection.

3.2. Development of the VBM sophistication dictionary

Our text-based measure of VBM sophistication captures the presence of VBM practices across a firm's annual reports. By aggregating n-gram frequencies (such as *value creation*) in textual corporate disclosures (here, annual reports) across five conceptually grounded VBM dimensions, the measure enables consistent and scalable firm-level comparisons. The frequency and distribution of these n-grams reflect the breadth and integration of VBM practices within the firm. This dictionary-based approach allows us to systematically quantify the linguistic expression of VBM sophistication in a scalable and consistent manner. We applied a five-step process to develop the dictionary. Fig. 1 illustrates the dictionary creation process.

First, we applied a deductive approach and collected theoretically anchored words related to VBM (Fig. 1 step 1). The origins of the VBM literature primarily trace back to consultants who pioneered and promoted their metrics for quantifying shareholder value creation (Bromwich and Walker, 1998; Davies, 2000). We reviewed the original literature on VBM to identify the various systems of measurement

Table 1
Sample selection.

Sample selection	
Listed firm-years of non-financial firms of the STOXX Europe 600 Index (2010–2018)	5356
Less firm-years of financial firms (SIC 6000–6999)	1197
Less firm-years with missing annual reports	553
Less firm-years with other data restrictions	1106
Firm-years included in the sample	2500

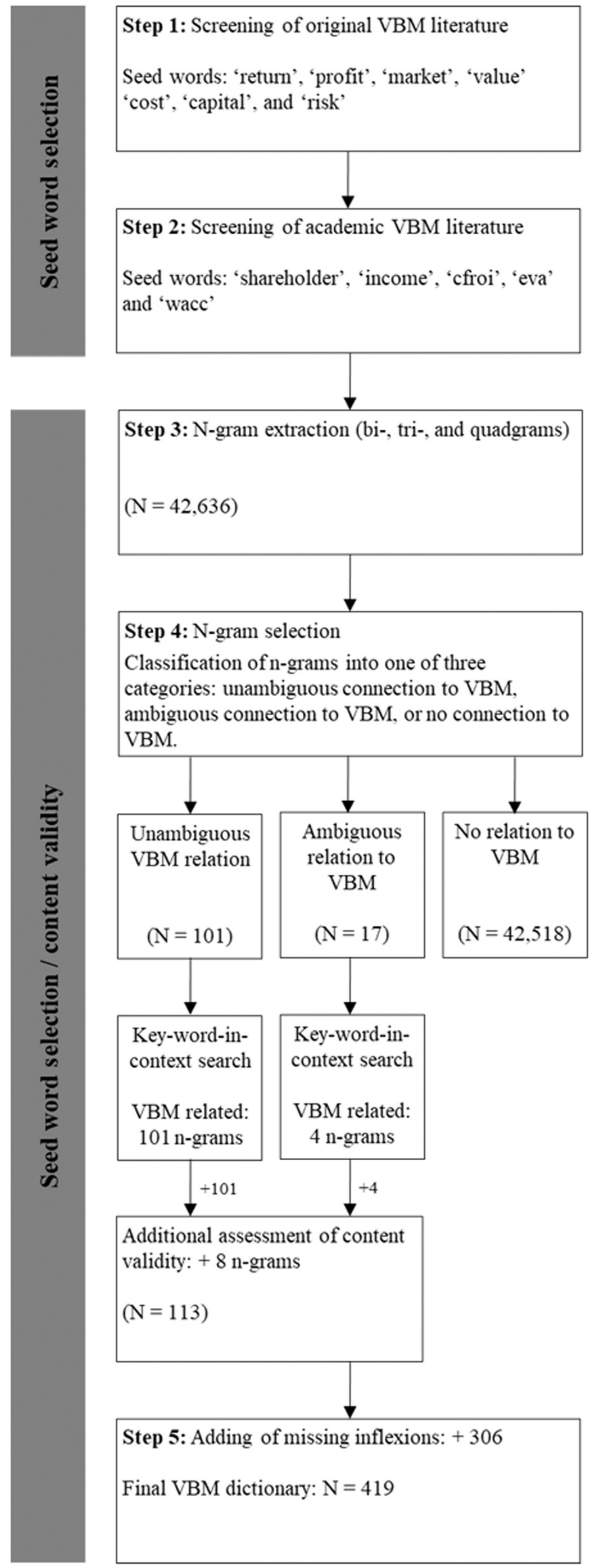

Fig. 1. Dictionary creation.

[7] We manually collected annual reports for 3606 firm-years during the extended collection period between March 2020 and May 2020.

[8] Occasionally, firms issue separate documents for their financial statements and for details regarding management, governance, and remuneration. In these cases, we consolidated these sections into a unified annual report for comprehensive analysis.

(Copeland et al., 1996; Madden, 1999; McTaggart et al., 1994; Rappaport, 1986; Stewart, 1991), and found the following prominent metrics: economic value added (EVA) (Stewart, 1991), cashflow return on investment (Madden, 1999), return on invested capital (Copeland et al., 1996), and shareholder value added (Rappaport, 1986), all of which align with the fundamental premise of VBM, namely to create returns above the cost of capital (Davies, 2000; Ittner and Larcker, 2001). We deconstructed these metrics into their underlying conceptual components and selected the terms most reflective of their logic to form an initial set of seed words[9]: ‘return’, ‘profit’, ‘market’, ‘value’, ‘cost’, ‘capital’, and ‘risk’. Seed words are a small set of conceptually meaningful terms that reflect the semantic core of the target construct (Li et al., 2021). Second, we supplemented the initial seed words by identifying additional VBM-relevant terms from the academic literature that were not captured through the disaggregation of VBM metrics (Fig. 1 step 2). We drew on the corpus of 77 peer-reviewed articles included in Wobst et al. (2025), who conducted a systematic literature review on the conceptualisation and measurement of VBM from 1979 to 2023.[10] Using the Linguistic Inquiry and Word Count (LIWC) 22 software,[11] we generated a list of all words that appeared in at least 20 % of these articles, resulting in a set of 2429 frequently used terms. We manually screened this list for any additional seed words not already included. Words were evaluated based on their definitional fit with VBM’s core principles, not merely on surface frequency. Most of the words were either too generic and therefore not relevant to VBM (e.g., ‘financial’, ‘management’, ‘firms’, ‘business’) or were already part of our initial list. Only five terms—‘shareholder’, ‘income’, ‘cfroi’, ‘eva’, and ‘wacc’—were identified as conceptually aligned with VBM and added to the seed list. The purpose of this second step was to validate the initial seed words and identify any additional literature-based terms that met our conceptual criteria for inclusion. The low number of inductively added terms reflects that the deductive phase already reached thematic saturation, which speaks in favour of content validity and robustness in our dictionary development. We then used LIWC-22’s integrated synonym finder to search for semantically related terms to our final set of seed words. However, the suggested synonyms (e.g., ‘revenue’, ‘expenditures’, ‘credit rating’, ‘currency’, ‘minimum wage’) lacked conceptual relevance and were not included in the seed word list. Thus, our final seed word list consisted of: “return”, “profit”, “market”, “value” “cost”, “capital”, “risk”, “shareholder”, “income”, “cfroi”, “eva”, and “wacc”.

Third, we augmented the deductive approach with an inductive approach (Fig. 1 step 3). This step was essential, as the seed words—-while conceptually central to VBM—are also frequently used in non-VBM contexts. Therefore, we used the seed words to set the boundaries of our measure and ensured that our measure was distinct from others. The inductive analysis extracted words that were used in conjunction with the seed words and reflected VBM. We began by extracting n-grams[12] from the annual reports of the firms listed on the STOXX Europe 600 Index during the period 2010–2018. Prior studies describe the superiority of using n-grams to better account for the context in which words appear (Andreou et al., 2020; Pandey and Pandey, 2019). We applied different pre-processing steps before extracting the n-grams (Hickman et al., 2022). Specifically, we removed punctuation marks, numbers, currency symbols, and junk characters (e.g., * + #) as not meaningful for our analysis. We also converted all data to lowercase (Bochkay et al., 2022; Hickman et al., 2022). To limit the analysis to the most frequently occurring n-grams, we restricted our extraction those of two to four words (bigrams, trigrams, and quadgrams) that occurred at least ten times in the underlying body of texts and which included at least one of our seed words (Kern et al., 2016; Speer, 2018; Yang et al., 2021). N-grams that appear less frequently are more likely to occur by chance and are presumably idiosyncratic to the underlying texts (Yang et al., 2021). Additionally, we restricted the placement of function words (e.g., ‘and’, ‘of’, ‘in’) to the interior of trigrams and quadgrams to improve semantic precision.[13] The algorithm produced 42,636 n-grams, all of which contained at least one of our seed words.[14]

Fourth, we assessed the content validity of the n-grams (Fig. 1 step 4). Content validity refers to the degree to which a measure captures the scope of the intended construct (Nunnally and Bernstein, 1994). One member of our research team manually screened the n-grams to ensure that they specifically reflected VBM-related concepts. For the development phase of the VBM sophistication dictionary, an n-gram was treated as having a clear connection to VBM if it captured one of the following key aspects of VBM: (1) value creation, which aligns with the principle of generating returns for shareholders; (2) opportunity cost, which highlights the importance of making decisions that generate returns above the capital costs; or (3) long-term strategic focus, emphasising long-term decision making. Where possible, we prioritised longer n-grams to enhance precision. For instance, when both *shareholder value* (bigram) and *create shareholder value* (trigram) appeared, we retained the latter, as it more effectively conveys the concept of VBM. The majority of n-grams were easily excluded during the initial screening, as they clearly did not align with any of the three core VBM dimensions and instead reflected unrelated concepts such as working capital management (e.g., ‘movement in working capital’, ‘reduction in working capital’), taxation (e.g., ‘taxable income’, ‘pre-tax income’, ‘provision for income taxes’), and general risk management (e.g., ‘comprehensive risk management’, ‘monitoring of risk’, ‘credit risk’). Although such n-grams all included seed words like ‘capital’, ‘income’, or ‘risk’, their usage in these contexts is clearly distinct from the conceptual foundations of VBM. Some n-grams could be unambiguously assigned to VBM (e.g., ‘create shareholder value’, ‘delivering sustainable shareholder value’, and ‘return to shareholders’), while others were more ambiguous in meaning and required further contextual review. Accordingly, the n-grams were classified into one of three categories: no connection to VBM (42,518 n-grams), unambiguous connection to VBM (101 n-grams), and ambiguous connection to VBM (17 n-grams). We applied a

[9] For example, we used the EVA formula (EVA = net operating profit after tax – [invested capital × weighted average cost of capital]) and selected words that best described the components of the formula. We identified the word ‘value’ as reflecting the economic value added by a firm above the cost of capital, ‘profit’ as capturing the net operating profit after tax, ‘capital’ as capturing the amount of money invested in the firm, and both ‘cost’ and ‘capital’ capture the weighted average cost of capital. We applied the same approach to the other identified metrics.

[10] The software was unable to process three of the articles, reducing the Wobst et al. (2025) sample from 80 to 77 articles. Before conducting the analysis, we used LIWC-22’s integrated stopword list to remove meaningless words such as *a*, *and*, *the*, and *is* that do not carry much meaning.

[11] LIWC_22 is a textual analysis tool that automatically processes and counts words and n-grams in textual data. It includes built-in dictionaries to measure psychosocial concepts and supports the creation of custom dictionaries through features such as keyword-in-context searches, a synonym finder, and diagnostic tools (Boyd et al., 2022). We utilised the *Meaning Extraction* module to identify the most commonly used words.

[12] We used the term *n-grams* to refer to bi-, tri-, and quadgrams in our analysis.

[13] We extracted the n-grams using the Natural Language Toolkit (NLTK version 3.6.1) Collocations module in Python. NLTK is an open-source library that facilitates working with natural language (Bird et al., 2009). The Collocation module offers a suitable approach for extracting concept-specific *n-grams* (i.e., sequences of words of length *n*).

[14] The substantial number of extracted n-grams reflects the scale of the underlying dataset, which comprises 3606 annual reports with an average word count of approximately 90,000. From this corpus, we identified only those unique n-grams that contained at least one of the predefined seed words, yielding a targeted yet still sizable set of candidate phrases. The relatively small number of seed words nonetheless produced a high number of unique n-grams due to the wide range of contextual expressions in which these seed terms appeared. The list included some semantic overlaps and structural redundancies. For instance, both the bigram *shareholder value* and the trigram *create shareholder value* appeared in the dataset.

Table 2
Overview of the most frequently occurring n-grams.

n-gram	Absolute frequency	Percentage of annual reports containing the n-gram	Example
value creation	8807	67 %	[…] it should be noted that the Company's remuneration policy does not provide for the deferred payment of all or part of the variable component of remuneration, and the Remuneration Committee believes that it has found, thus far, the mechanisms that allow the alignment of the interests of the Executive Directors with the long-term interests of the Company and the Shareholders, enabling the sustained growth of the Company's business and the corresponding value creation for the Shareholders. (Annual Report 2012, p. 139, Jerónimo Martins)
shareholder return(s)	7992	58 %	Our focus continues to be on generating shareholder returns through prudent capital allocation, with a focus on low-risk, phased projects with high returns. (Annual Report 2013, p. 9, Vedanta Resources)
cost of capital	7865	78 %	The ROCE target is aligned with the company's financial planning and is significantly higher than its cost of capital. (Annual Report 2013/2014, p. 47, Sonova)
wacc	4648	45 %	The metric used for the value-added target will be ROACE relative to WACC. (Annual Report 2010, p. 171, E.ON)
create value	3519	50 %	Material themes are those that substantially affect BAM's ability to create value over the short, medium and long term. (Annual Report 2015, p. 8, BAM)
economic value	2168	33 %	As part of the process of developing the Group's management system, "economic value added" has been introduced at Group level as a new key performance indicator. (Annual Report 2010, p. 47, BMW)
risk premium	1902	37 %	The basic variables in the model are interest rate level, general risk premium and the so-called beta risk on the Elisa share. (Annual Report 2015, p. 157, Elisa)
creating value	1895	33 %	AIXTRON is committed to observing the principles of transparent and responsible conduct of its business aimed at creating value on a sustainable basis by employing appropriate corporate governance. (Annual Report 2015, p. 18, AIXTRON)
risk-free interest rate	1770	36 %	The employee stock option plan is measured at fair value at the date of grant. Fair value reflects the parameters of the compensation plan, the risk-free interest rate, the expected volatility, the dividend yield and the early exercise experience of the Group's plans. (Annual Report 2017, p. 192, Coca-Cola HBC)
capital allocation	1493	36 %	We pursue greater value for shareholders and optimise future capital allocation by prioritising and investing in only the highest returning projects. (Annual Report 2012, p. 75, Rio Tinto)

keyword-in-context analysis to n-grams identified through manual conceptual review as either unambiguous (n = 101) or ambiguous (n = 17). The purpose of a keyword-in-context analysis is to examine n-grams within their surrounding text to determine their appropriateness for inclusion or exclusion.[15] Following Belderbos et al. (2017), we manually reviewed 50 random sentences per n-gram, only retaining those that appeared in over 75 % of cases. The n-grams that did not occur in a VBM context are considered 'out of context' (Belderbos et al., 2017). For example, firms often use the term *value system* to refer to their ethical principles and values rather than their VBM practices. For unambiguous cases that appeared in different grammatical or morphological variants, the analysis was conducted on a representative form (e.g., *create shareholder value*), while related variants (e.g., *created or creating shareholder value*, or singular/plural forms such as *opportunity cost / opportunity costs*) were treated as conceptually equivalent within the VBM context. This procedure resulted in a keyword-in-context analysis of 47 unambiguous n-grams, all of which were confirmed to consistently occur in a VBM context. For the ambiguous cases, we eliminated 13 out of the 17, as these were considered out of context. In total, we retained 105 n-grams (101 from the unambiguous cases and 4 from the ambiguous ones). To enhance the content validity, one member of the research team not yet involved in the dictionary generation process and an independent research assistant assessed the preliminary dictionary. They were asked to add or delete n-grams, or to provide general comments. Neither deleted any n-grams, but both made suggestions for additional n-grams (eight in total).[16] Thus, we included 113 n-grams in the dictionary.

Fifth, we added missing inflexions (Fig. 1 step 5). For example, we added the n-gram *created shareholder value* because the algorithm only extracted the n-gram *create shareholder value.* Generally, there are two approaches to account for the different morphological variants of dictionary n-grams: including different inflexions in the dictionary, or only including word stems (Bannier et al., 2019). Loughran and McDonald (2016) suggest including explicit inflexions to remedy errors occurring from stemming algorithms. Moreover, the dictionary considers the differences between American and British spelling. Consequently, we added 306 n-grams. In total, our VBM sophistication dictionary contains 419 n-grams (see Appendix C for the full dictionary).

3.3. Fit of the dictionary with the definitions of VBM(-sophistication)

Our *deductive* seed-word approach ensured that the dictionary aligns with our academic definitions of VBM sophistication. The *inductive* expansion complemented this by aligning the dictionary with the terminology used by firms. Table 2 presents the ten most frequently occurring n-grams with illustrative example sentences. The most frequently appearing n-gram is *value creation*, which occurs 8807 times

[15] We used the LIWC-22 contextualiser tool for this analysis, which displays the ten words preceding and following each *n-gram*.

[16] The following eight n-grams were included: *idiosyncratic risk*, *idiosyncratic risks*, *residual income*, *unsystematic risk*, *unsystematic risks*, *value based management*, *value-based management*, *capm*.

and appears in 67 % of the annual reports. N-grams such as *cost of capital* and *wacc* are also commonly used, showing the importance of financial metrics for VBM.[17]

(1) Core financial metrics such as *economic value* (Table 2, n = 2168), *wacc* (Table 2, n = 4648), *risk-free interest rate* (Table 2, n = 1770), *economic profit*, *residual income*, *EVA*, and *CFROI* are integral to the quantification of *value creation* (Table 2, n = 8807). These dictionary terms encapsulate the tools essential for measuring the outcomes of VBM and aligning shareholder value with strategic goals.

(2) Target setting is reflected in n-grams such as *delivering value*, *value enhancement*, and *generation of value*, which highlight dynamic processes such as target setting and action plans rather than static objectives such as KPIs. These terms demonstrate an ongoing commitment to initiatives designed to align with and achieve value-maximising targets.

(3) Operational integration is captured through terms such as *value contribution* and *capital allocation* (Table 2, n = 1493), which are essential for embedding VBM principles into daily operations. These terms link strategic objectives with actionable, value-creating activities, ensuring that organisational goals are translated into concrete operational practices.

(4) Compensation linking involves aligning managerial and employee compensation with value-based outcomes by tying incentives to performance metrics. While our dictionary does not explicitly include generic terms such as bonus, incentive, reward, remuneration, performance pay, or equity compensation—common in all annual reports, even those of firms with low VBM sophistication—it reflects VBM-specific links to compensation. It does so through terms such as *return to shareholders*, *shareholder return(s)* (Table 2, n = 7992), *risk premium* (Table 2, n = 1902) and *value delivery*, which suggest direct connections between firm performance and stakeholder outcomes. Prior research (e.g., Ryan and Trahan, 2007) has shown that compensation systems in VBM-oriented firms frequently incorporate metrics such as *cost of capital* (Table 2, n = 7865), capital charge, or shareholder return(s)—several of which are represented in our dictionary. Additionally, phrases like *required rate of return*, *capital charge, and cost of equity* refer to financial metrics that are integral to compensation models that meet or surpass risk benchmarks, a defining feature of VBM compensation.

(5) Value orientation and culture are captured through terms such as *create value* (Table 2, n = 3519), *creating value* (Table 2, n = 1895), *value building*, *value driver*, *value-driven*, *create long-term value*, and phrases centred on *shareholder value*. These words underscore the importance of value-oriented thinking in guiding both strategic and operational decisions. Their presence aligns closely with the emphasis on cultivating a value-based mindset, as outlined in our definition.

Our dictionary deduces *depth*—as defined in Section 2.2—from annual report language by tracing how VBM terminology vertically spans from the top executive levels down to lower hierarchical levels. An example is the frequent use of terms such as *value delivery*, which would indicate the application of VBM in operational decision-making. Our dictionary deduces *breadth* by tracing how VBM terminology horizontally spans across functional areas such as finance, operations, and strategy. An example is the frequent use of terms such as *capital allocation*, indicating the application of VBM beyond the finance function.

4. Descriptive evidence

Table 3 displays the descriptive results of VBM sophistication across industries, countries, and years. The average VBM sophistication differs across industries. The utilities sector shows the highest average usage of VBM n-grams (39), but its firms also produce some of the longest annual reports on average (123,365 total words). The healthcare sector has the lowest average use of VBM n-grams (21), while also producing the shortest annual reports on average (79,759 total words). The standard deviations and the range between minimum and maximum values of VBM n-grams also suggest noticeable variation within industries. These fluctuations, both within and across different industries, align with the findings presented by Firk et al. (2019c). Furthermore, there are some differences in the national averages of VBM n-gram usage. Portugal shows the highest average use of VBM n-grams (89) but also produces some of the longest annual reports on average (113,295 words). Luxembourg has the lowest average use of VBM n-grams (11). In contrast, Firk et al. (2019c) identified Germany as having the highest VBM sophistication, with Portugal ranking lowest—a divergence that may be attributed to differences in the periods studied and the number of data points analysed in each group. Countries with comparable economic profiles, such as Austria and Germany, rank highly in terms of VBM n-grams use in both cases. Overall, Table 3 reveals that variation in VBM sophistication exists both between and within clusters of firms. The former, *inter*-cluster variation shows that VBM sophistication differs systematically across industries and countries. The *intra*-cluster variation reveals that even within these contextual boundaries, notable firm-level diversity persists. Together, these patterns suggest that firm-specific characteristics exert an additional, independent influence on VBM sophistication.Table 3 also shows that the mean use of VBM n-grams use increases over time, broadly consistent with the intra-cluster variation.

We also examined the average year-on-year change in the VBM measure. The average year-on-year change in overall report length is 10,201 words. In comparison, the number of VBM-related n-grams only fluctuates by approximately seven per year. These results suggest that, while there is some variation in the use of VBM-related language within firms over time, this variation is small compared to fluctuations in overall report length. Thus, despite some year-to-year changes, the VBM sophistication measure appears fairly persistent over time. Following Jennings et al. (2024), we regress the VBM measure on firm fixed effects to assess the degree to which it reflects stable, firm-specific characteristics. The R^2 of 0.71 indicates that the measure captures considerable between-firm variation, well below the 90 % threshold beyond which fixed effects may distort inference (Jennings et al., 2024). This is also consistent with the average year-on-year change in our VBM score of seven n-grams. Taken together, the results suggest that VBM sophistication reflects a moderately persistent firm-level orientation, while still allowing for meaningful within-firm variation—thereby justifying the use of panel regression with firm fixed effects.

5. Validation of the text-based VBM measure

We used the LIWC 2022 software to create our text-based measure because it enabled an analysis of different n-grams. The output is a continuous variable that calculates, for each report, the percentage of dictionary words relative to the total word count (Boyd et al., 2022). Scaling the dictionary count by total words is a common practice in NLP research to control for varying word lengths of the source documents (Loughran and McDonald, 2016; Short et al., 2010; Short et al., 2018). In our case, lengthy reports are more likely to include VBM-related n-grams, which can lead to higher VBM sophistication scores because of report length rather than genuinely higher VBM sophistication.

[17] Table 2 supports the notion that firms frequently discuss their VBM approaches in annual reports. For example, in Lufthansa AG's annual report for 2015, VBM is extensively discussed as part of the firm's broader financial strategy and management practices. The firm outlines its updated VBM approach by introducing new metrics aimed at improving the measurement and transparency of value creation, as well as describing the deep integration of these measures within the firm. The evidence supports our claim that the measure captures our definition above of VBM sophistication. Further examples of annual reports with sophisticated VBM practices include: Thyssenkrupp AG (2010), Volkswagen AG (2011), IMI PLC (2012), Anglo American PLC (2013), Lufthansa AG (2014), Ferrovial SE (2015), Wienerberger AG (2016), Clariant AG (2017), and BASF SE (2018).

Table 3
Descriptive statistics: VBM sophistication by industry, country, and year.

	Mean (total words)	Mean (VBM n-grams)	Median (VBM n-grams)	Std. (VBM n-grams)	Min (VBM n-grams)	Max (VBM n-grams)	No. reports (VBM n-grams)
Industry cluster (Fama & French 10)							
Consumer (non-durables)	88,481	24	21	16	1	72	239
Consumer (durables)	124,945	35	28	31	3	121	74
Manufacturing	81,950	28	21	23	0	169	698
Energy	99,220	28	23	18	0	76	120
Computers, Software & Electronic Equipment	85,618	23	19	17	0	105	199
Telecommunications	94,188	24	20	15	0	75	167
Wholesale	85,040	27	21	25	0	202	242
Healthcare	79,759	21	17	17	0	75	197
Utilities	123,365	39	35	17	10	75	89
Mining, Construction, Transportation, etc.	98,170	27	21	36	1	669	475
Total							2500
Country cluster							
Austria	60,758	34	22	34	2	124	45
Belgium	75,968	29	23	19	6	95	55
Denmark	47,548	18	13	17	2	72	79
Finland	66,969	24	21	23	0	128	115
France	144,543	19	16	13	0	76	397
Germany	96,133	34	28	27	1	169	335
Greece	63,820	26	17	43	4	231	26
Ireland	80670	29	23	23	2	76	37
Italy	108,442	24	21	17	4	75	78
Luxemburg	88,844	11	11	5	5	25	24
Netherlands	86,242	29	24	27	0	246	162
Norway	78,948	28	26	16	4	68	69
Portugal	113,295	89	66	69	22	202	11
Spain	73,288	33	19	84	0	669	62
Sweden	66,234	23	20	16	0	80	166
Switzerland	59,911	24	18	22	0	136	143
United Kingdom	83,630	28	26	15	0	93	696
Total							2500
Year cluster							
2010	78,938	20	16	17	0	99	268
2011	81,399	22	18	18	0	111	274
2012	85,704	23	19	18	0	116	283
2013	88,670	24	21	17	0	106	284
2014	90,029	27	23	20	0	130	283
2015	89,729	27	22	20	0	132	280
2016	94,204	29	23	22	0	137	282
2017	100,794	32	26	27	1	246	277
2018	104,786	37	30	47	2	669	269
Total							2500

5.1. Internal consistency

We assessed the internal consistency of the dictionary using the *Kuder-Richardson Formula 20* (KR-20) (Kuder and Richardson, 1937).[18] The KR-20 is particularly well-suited for binary data, such as the presence or absence of words or phrases across texts. The KR-20 yields a value of 0.734. Values above 0.50 indicate high internal consistency (Pennebaker, 2022). Internal consistency indicates how well the dictionary n-grams reflect a common construct (Boyd et al., 2022). The Kuder-Richardson formula evaluates the extent to which n-grams in a dictionary consistently co-occur across texts. We measured how frequently VBM-related n-grams appeared in annual reports and calculated the intercorrelations of these n-grams using LIWC-22. The rationale behind the formula is that the presence of one VBM-related n-gram in a text makes the occurrence of other VBM-related n-grams more likely (Boyd et al., 2022). For example, if a firm mentions n-grams like *value creation*, it is also likely to mention related n-grams like *cost of capital* and *risk-free interest rate*. This pattern indicates that the dictionary consistently captures VBM as a common underlying construct. Unlike Cronbach's alpha—which relies on word counts and can be misleading when some words appear much more often than others—KR-20 is better suited for text data. It only checks whether a word is present, which makes it more reliable when words are used rarely or only once (Boyd et al., 2022).

5.2. Construct validity

We validated our measure by assessing its convergent validity with hand-collected data, by replicating previously established relationships, and by conducting robustness tests.

5.2.1. Convergent validity with manually-coded data: full sample

Convergent validity describes the correlation between two measures of a similar construct (Campbell and Fiske, 1959). Therefore, we needed an external benchmark. We are grateful to have been allowed access to a subsample of Firk et al.'s (2019c) manually coded VBM sophistication data. They selected the 500 largest firms by market capitalisation from the STOXX Europe Total Market Index for the period 2005–2014. Firk et al. (2021) use the same VBM sophistication measure but extend the sample period to 2016. Since we used the full STOXX Europe 600 Index, there was an overlap of 1619 firm-year observations from 2010 to 2016 between our sample and theirs. The Firk et al. (2019c) VBM sophistication measure is a composite index, consisting of five different

[18] The Formula KR-20 is defined as $\propto_{KR-20} = \frac{k}{k-1}\left(1 - \frac{\sum_{j=1}^{k} p_j q_j}{\sigma^2}\right)$, where k is the number of items (n-grams), p_j is the proportion of documents in which item j appears, $q_j = 1 - p_j$ and σ^2 is the variance of total scores (i.e., the number of n-grams present per document).

elements: 1 = value orientation, 2 = value-based metric adoption, 3 = target setting, 4 = compensation linking, and, 5 = operational integration. These elements are summed up across binary-coded categories. They collected the relevant information by conducting a manual content analysis of annual reports. We performed a Spearman's correlation to assess the convergent validity of our text-based measure. The results display a significant ($p < 0.01$) correlation of 0.54, which reflects a large effect size (Cohen, 1988). Prior research recognises convergent validity if the text-based indicator displays a positive and significant relationship with the alternative measure (Belderbos et al., 2017; McKenny et al., 2013). The correlation of 0.54 exceeds the convergent validity findings of previously established studies, which typically

Table 4
Distribution across quintiles.

Panel A

	Quintiles of this study's text-based VBM sophistication measure				
	1	2	3	4	5
Quintiles of Firk et al. (2019): 1	**94.75%**	83.64%	79.32%	73.15%	47.06%
2	0.00%	0.00%	0.00%	0.00%	0.00%
3	0.00%	0.00%	0.00%	0.00%	0.00%
4	4.32%	7.41%	10.80%	11.42%	17.03%
5	4.32%	8.95%	9.88%	15.43%	**35.91%**
Total (%)	100.00%	100.00%	100.00%	100.00%	100.00%
Absolut	324	324	324	324	323

Panel B

Lowest quintile agreement *(94.75 %)*		**Drivers of lower agreement**		**Highest quintile agreement** *(35.91 %)*	
Top 20 N-grams	Absolute frequency			Top 20 N-grams	Absolute frequency
cost of capital	333			cost of capital	1615
value creation	327			wacc	695
risk free interest rate	224			value creation	464
wacc	185			shareholder return	419
shareholder return	132		+	**economic value**	244
create value	126			create value	229
cost of debt	122			cost of debt	192
risk free rate	117		+	**eva**	181
risk premium	96			risk premium	177
creating value	90		¶	**value management**	177
economic value	81		¶	**value based management**	171
increase in value	37		¶	**cost of equity**	167
eva	34			value enhancing	125
creation of value	32		–	**risk free interest rate**	114
value created	31			value created	113
return to shareholders	31	§		value enhancement	112
protect the value	29	§		value creating	100
value generated	28			creating value	98
creates value	26			value contribution	89

Notes: Panel B reports the frequency with which each n-gram occurs in the bottom and top quintiles. It highlights the n-grams that drive differences in agreement across quintiles. The column "Drivers of lower agreement" in the top quintile applies the following notation: (+) terms more emphasized relative to the bottom quintile; (–) terms less emphasized relative to the bottom quintile; (¶) terms that newly appear in the top quintile; and (§) terms from the bottom quintile that do not appear among the most relevant terms in the top quintile.

reported scores ranging between 0.15 and 0.40 (e.g., Belderbos et al., 2017; Gamache et al., 2015; McKenny et al., 2013). Thus, we conclude that our VBM sophistication measure demonstrates satisfactory convergent validity.

5.2.2. Convergent validity with manually-coded data: quintile analysis

Panel A of Table 4 shows the percentage of observations from our VBM sophistication measure that fall into the same or different quintiles as the VBM sophistication benchmark by Firk et al. (2019c) for the overlapping subsample. The results indicate a strong agreement between the two measures at the lower end of the distribution: 94.75 % of the observations classified in the lowest quintile according to our measure also appear in the lowest quintile by the measure of Firk et al. (2019c). The high agreement is only partially due to zero values, as the correlation still holds at 85 % after excluding zeros. A small percentage (4.32 %) of the observations in our lowest quintile appear in the 4th or 5th quintiles of the Firk et al. (2019c) measure, while none appear in the 2nd and 3rd quintiles. The level of agreement decreases for higher quintiles. Only 35.91 % of the observations in our highest quintile are also found in the highest quintile according to the Firk et al. (2019c) measure, while 47.06 % of the observations classified in the highest quintile by our measure are placed in the lowest quintile by Firk et al. (2019c). These findings suggest that although the two VBM sophistication measures exhibit substantial agreement in identifying firms with minimal VBM sophistication (i.e., in the lowest quintiles), they diverge in the classification of firms with higher VBM sophistication.

Panel B of Table 4 reports the frequency of the twenty most common n-grams in the bottom quintile, where the agreement between our dictionary measure and the benchmark measure by Firk et al. (2019c) is very high (94.75 % agreement), and in the top quintile, where agreement is lower (35.91 % agreement). In particular, the column '*Drivers of lower agreement*' identifies which terms are emphasised, de-emphasised, or newly introduced/omitted in the top quintile relative to the bottom quintile.

Regarding areas of agreement, many of the core VBM terms (e.g., *cost of capital*, *value creation*) appear in both quintiles, although with substantially higher frequency in the top quintile. Some terms scattered across both quintiles exhibit minor variations of a shared concept (e.g., *creating value* in the bottom quintile and *value creation* in the top quintile). All these terms explain the strong convergence of both measures in the bottom quintile.

The differences emerge at the upper end of the distribution. Certain terms are relatively less frequent in the top quintile, such as *risk-free rate*, which reflects a comparatively basic input to VBM calculations. Firms signal higher sophistication by explaining details on their cost of equity capital assessment, featuring terms such as *economic value* and *EVA*. Such information is less readily available and therefore indicative of higher sophistication.

Some terms disappear when moving from the bottom to the top quintile. The disappearing term *protect the value* is defensive and loss-oriented. The equally disappearing term *return to shareholders* evokes a narrative in which annual reports must explicitly assert shareholder claims, which requires relatively less emphasis among sophisticated VBM firms.

Some terms appear only in the top quintile, for example *value management*, *value-based management*, and *cost of equity*—the latter implying complex cost-of-capital calculations. These terms address a strategic level because they emphasise the management of value rather than its technical measurement. They also function as signals to educated investors, since the term VBM is academic in origin and has only weakly diffused into practice (Wobst et al., 2025).

Taken together, our measure is complementary to Firk et al. (2019c). In the bottom quintile, both measures provide a reliable way of identifying firms that reference the basic financial anchors of VBM. In the top quintile, differences emerge. Our measure emphasises advanced cost-of-capital terminology (*EVA*, *economic value added*) and strategic terms (e.g., *VBM*). It also reflects external communication and signalling of VBM-related practices through academic language that is only weakly diffused into practice. Yet, our broader scope comes at the cost of a more demanding argument about validity. Depending on their research objective, researchers should choose between the measure by Firk et al. (2019c), which offers a lean and robust benchmark for operational cost-of-capital orientation, and our approach, oriented toward the wider strategic discourse surrounding VBM.

5.2.3. Replication of performance effects of VBM: accounting-based measure

We next further assess convergent validity by replicating established relationships between VBM sophistication, its antecedents, and firm performance. In line with Wobst et al.'s (2025) literature review, we identified nine studies that particularly investigate how firm performance is driven by (the disclosure of) VBM practices and VBM *sophistication* (Bezemer et al., 2015; Brück et al., 2023; Firk et al., 2021; Firk et al., 2019b, c; Firk et al., 2016; Ittner et al., 2003; Mavropulo et al., 2021; Schultze et al., 2018). We used ***return on assets***, calculated as operating income divided by total assets, as our firm performance measure (Bezemer et al., 2015; Brück et al., 2023; Firk et al., 2021; Firk et al., 2019b, c; Ittner et al., 2003; Schultze et al., 2018). Our text-based VBM sophistication measure, which represents the percentage of dictionary n-grams in each firm's annual reports, is our independent variable.

To increase the comparability with prior studies on VBM and firm performance (Wobst et al., 2025), we included the following standard firm-level controls:

- *size* (here, natural logarithm of total assets) (Bezemer et al., 2015; Brück et al., 2023; Firk et al., 2021; Firk et al., 2019b, c; Firk et al., 2016; Ittner et al., 2003; Mavropulo et al., 2021; Schultze et al., 2018),
- *leverage* (here, total debt divided by total assets) (Bezemer et al., 2015; Brück et al., 2023; Firk et al., 2021; Firk et al., 2019b, c; Firk et al., 2016; Mavropulo et al., 2021; Schultze et al., 2018),
- *diversification* (here, entropy measure of segment sales) (Firk et al., 2021; Firk et al., 2019c; Firk et al., 2016; Jacquemin and Berry, 1979),
- *capital intensity* (here, property, plant and equipment divided by total assets) (Firk et al., 2021; Firk et al., 2019c; Firk et al., 2016; Mavropulo et al., 2021), and
- *foreign sales* (here, natural logarithm of foreign sales divided by sales) (Bezemer et al., 2015; Brück et al., 2023; Schultze et al., 2018),
- *board size* (here, number of board members) as this may affect firm performance through monitoring and controlling activities (Firk et al., 2021; Firk et al., 2016), and the
- *largest owner* (here, percentage held by the largest owner) (Bezemer et al., 2015; Brück et al., 2023; Firk et al., 2021; Firk et al., 2019b; Firk et al., 2016) as owners can influence strategic choice and firm performance (Fiss and Zajac, 2004).

We ran a fixed-effects regression using time and firm-fixed effects. Firm-fixed effects control for time-invariant, unobservable firm-specific characteristics, which are a potential source of endogeneity. This is particularly relevant, as firms' implementation of management practices such as VBM can be an endogenous choice (Hennig et al., 2023; Mavropulo et al., 2021). We also winsorised all continuous variables at their 1st and 99th percentiles to reduce the effect of outliers.

We estimated several regression models to assess the validity. First, we investigated the effect of VBM sophistication on firm performance using our text-based variable in the baseline model. Model 1 of Table 5 reveals a statistically significant, positive coefficient of VBM sophistication. Economically, a one standard deviation change in VBM sophistication increases firm performance by approximately 9 % of its standard deviation. Second, we used an alternative specification of the

Table 5
Performance effect of VBM sophistication.

Model	1	2	3
Dependent variable	Return on assets	Return on assets	Return on assets
VBM sophistication	0.151***		
	(4.504)		
VBM sophistication (raw count)		0.000***	
		(3.128)	
VBM sophistication (benchmark)			0.003**
			(1.979)
Total word count		−0.000**	
		(−2.205)	
Size	−0.0164**	−0.0161**	−0.014
	(−2.390)	(−2.340)	(−1.351)
Leverage	−0.185***	−0.184***	−0.208***
	(−8.139)	(−8.121)	(−6.353)
Diversification	0.003	0.00337	0.007
	(0.807)	(0.907)	(1.607)
Board size	−0.001	−0.000520	−0.000
	(−0.814)	(−0.714)	(−0.148)
Capital intensity	−0.040	−0.0401	−0.085*
	(−1.299)	(−1.288)	(−1.957)
Foreign sales	−0.019***	−0.019***	−0.029***
	(−5.029)	(−5.065)	(−5.631)
Largest owner	0.000	0.000	−0.000
	(0.360)	(0.335)	(−0.916)
Constant	0.153	0.153	0.000
	(1.049)	(1.045)	−0.001
Firm effects	Yes	Yes	Yes
Year effects	Yes	Yes	Yes
Adj. r-squared	0.69	0.69	0.73
N	2500	2500	1503

Notes: ***, **, and * indicate statistical significance at the 1 %, 5 %, and 10 % levels (two-tailed). T-statistics are displayed below the coefficients in parentheses. All continuous variables are winsorised at the 1 % and 99 % level. All models are estimated using fixed-effects regressions. Standard errors are heteroskedasticity-robust. *Return on assets* = operating income divided by total assets. *VBM sophistication* = sum of dictionary count calculated as percentage of total word count. *Size* = natural logarithm of total assets. *Leverage* = total debt divided by total assets. *Diversification* = entropy measure of segment sales. *Board size* = number of board members. *Capital intensity* = property, plant and equipment divided by total assets. *Foreign sales* = natural logarithm of foreign sales divided by sales. *Largest owner* = percentage held by largest owner. *VBM sophistication (raw count)* = dictionary raw account per annual report. *VBM sophistication (benchmark)* = manually coded VBM sophistication measure by Firk et al. (2019c). *Total word count* = raw count of total words per annual report.

text-based measure to verify that our findings were not influenced by the construction of our text-based variable. In Model 2, we included the raw count of the dictionary n-grams and accounted for annual report length by including total word count as a separate control variable. The findings are consistent with those from Model 1. Third, we assessed whether we obtained comparable results when using Firk et al.'s (2019c) VBM sophistication measure instead of our text-based measure. Model 3 of Table 5 displays comparable results by yielding a statistically significant and positive coefficient for the VBM sophistication benchmark. Overall, the results confirm previous findings (Firk et al., 2019c; Firk et al., 2016) and support the validity of our text-based measure.

5.2.4. *Replication of performance effects of VBM: market-based measure*

Following Firk et al. (2016), we used the market-to-book ratio as an alternative measure for firm performance. We measured the *market-to-book ratio* as the market capitalisation divided by common equity (Firk et al., 2019c). We then reanalysed the baseline effect of VBM sophistication (Model 1 in Table 5) using the alternative dependent variable. The results showed a significant, positive coefficient of 0.61 ($p < 0.05$), confirming the positive performance effect of VBM sophistication (not tabulated).

Table 6
Determinants of VBM sophistication.

Model	4	5	6
Dependent variable	VBM sophistication	VBM sophistication (benchmark)	VBM sophistication (raw count)
Capital intensity	0.026***	1.682**	12.374***
	(2.701)	(2.440)	(2.659)
Size	−0.001	0.122	1.725***
	(−0.374)	(1.388)	(2.620)
Leverage	0.015	−0.049	6.287
	(1.115)	(−0.056)	(1.155)
Return on invested capital	0.000	0.005	0.034
	(1.024)	(0.638)	(0.604)
Largest owner	−0.000***	−0.021***	−0.153***
	(−4.239)	(−2.970)	(−2.921)
Beta	−0.001	0.300	−0.079
	(−0.232)	(1.161)	(−0.042)
Profit margin	0.000	−0.008	0.002
	(0.426)	(−1.050)	(0.043)
Total word count			0.000***
			(5.244)
Industry effects	Yes	Yes	Yes
Year effects	Yes	Yes	Yes
Adj. r-squared /pseudo r-squared	0.08	0.03	0.17
N	2500	1507	2500

Notes: ***, **, and * indicate statistical significance at the 1 %, 5 %, and 10 % levels (two-tailed). T-statistics are displayed below the coefficients in parentheses. All continuous variables are winsorised at the 1 % and 99 % level. Model 4 is estimated using a fixed-effects regression and Model 5 using an ordinal logit regression. Industry effects consist of 10 Fama & French industry dummies. The ordinal nature and stability of VBM sophistication over time precluded the control for firm-fixed effects (Firk et al., 2019c). Standard errors are clustered at the firm-level. Intercepts are not reported. *VBM sophistication* = sum of dictionary count calculated as percentage of total word count. *VBM sophistication (raw count)* = dictionary raw account per annual report. *Capital intensity* = property, plant and equipment divided by total assets. *Size* = natural logarithm of total assets. *Leverage* = total debt divided by total assets. *Return on invested capital* = (net income - bottom line + (interest expense on debt - interest capitalised) * (1-tax rate)) / average of last year's and current year's (total capital + short term debt and current portion of long term debt) * 100). *Largest owner* = percentage held by the largest owner. *Beta* = 36 months rolling beta of the local market index provided by Datastream. *Profit margin* = operating profit margin calculated as operating income divided by sales multiplied by 100. *Total word count* = raw count of total words per annual report.

5.2.5. *Replication of antecedents' effects on VBM: capital intensity*

We evaluated whether factors previously shown to influence VBM sophistication also affect it when measured with our text-based measure. Like Firk et al. (2019c), we investigated whether capital intensity drives VBM sophistication. We estimated two further models: Model 4 assesses the effect of capital intensity on VBM sophistication using the text-based variable, and Model 5 uses Firk et al.'s (2019c) VBM sophistication variable. We measured *capital intensity* by dividing property, plant and equipment by total assets. We screened the literature on determinants of VBM and selected commonly used controls (e.g., Brück et al., 2023; Firk et al., 2019c; Firk et al., 2016). The following variables were included: firm *size* (natural logarithm of total assets), *leverage* (total debt divided by total assets), *return on invested capital* (net income - bottom line +

(interest expense on debt – interest capitalised) x (1-tax rate)) / average of last year's and current year's (total capital + short-term debt and current portion of long-term debt) x 100), *largest owner* (percentage held by the largest owner), *beta* (a 36 months rolling beta of the local market index provided by Datastream), and *profit margin* (operating profit margin calculated as operating income divided by sales multiplied by 100). We used a fixed-effects regression for Model 4 and an ordinal logit regression for Model 5 to account for the ordinal nature of Firk et al.'s (2019c) VBM sophistication variable. We included industry and year-fixed effects in Models 4–6. Following Firk et al. (2019c), we applied industry rather than firm-fixed effects, because the original VBM sophistication variable is ordinal and exhibits only limited within-firm variation over time. This specification avoids overfitting from time-invariant firm characteristics while ensuring comparability with the benchmark study. Table 6 shows that all models indicate a significant and positive effect of capital intensity on VBM sophistication. The results are in line with prior research and therefore validate our text-based measure (Firk et al., 2019c).

5.2.6. *Robustness test: reverse causality of financial performance*

We then addressed the potential issue of endogeneity when analysing the performance effects of management practices (Firk et al., 2019c; Firk et al., 2016). We tested our baseline effect using Generalised Method of Moments (GMM) estimators to mitigate endogeneity concerns such as unobserved, time-invariant firm characteristics, simultaneity, and dynamic endogeneity (Arellano and Bond, 1991; Ullah et al., 2018; Wintoki et al., 2012).[19] It is plausible that high-performing firms are more likely to espouse higher VBM sophistication (reverse causality) and that past realisations of our dependent variable drive the relationship between VBM and firm performance (dynamic endogeneity) (Firk et al., 2019b, c; Firk et al., 2016). The GMM uses instruments derived from the existing econometric model and allows the inclusion of a lagged dependent variable to address endogeneity (Roodman, 2009a; Wintoki et al., 2012). The results yielded a significant and positive coefficient of 0.299 ($p < 0.05$), which further supports construct validity (not tabulated).

5.2.7. *Robustness test: disclosure bias*

Last, we addressed a potential disclosure bias in our VBM sophistication measure that may artificially inflate variation within firms. Management control systems such as VBM are typically implemented and revised gradually, resulting in relatively stable patterns over time (Malmi and Brown, 2008; Otley, 1999; Simons, 1994). Because our measure is based on annual report language, it may temporarily spike in years when firms revise or update their disclosures. Such episodic spikes risk overstating changes in VBM sophistication and introduce artificial volatility within firms. To mitigate this, we adjusted the measurement specification to dampen short-term fluctuations and re-estimated Model 2 using the modified values. Specifically, we identified firm-year observations as temporary spikes if the VBM measure in a given year was significantly higher—by more than the average year-on-year change in our sample (seven n-grams)—than in both the previous and the subsequent year. For these identified spikes, we adjusted the value downward, bringing it closer to the level of the subsequent year.[20] We re-estimated Model 2 using the adjusted VBM sophistication measure and obtained similar results, with a positive and statistically significant coefficient of 0.0003 ($p < 0.01$). These findings suggest that our results are robust to any temporary spikes in VBM-related reporting (not tabulated).

6. Discussion and conclusion

This study responds to prior research calls and proposes a new approach for measuring VBM sophistication (Firk et al., 2021; Shin and You, 2017; Wobst et al., 2025). We demonstrate that NLP methods reliably quantify VBM sophistication. This approach complements existing ones by providing an alternative that facilitates time-efficient, large-scale, and longitudinal analyses.

6.1. *Contributions*

This study contributes to research in several ways. First, we develop and share a customised VBM sophistication dictionary to support future research. This tool complements existing measurement approaches such as surveys or manual content analyses by offering a scalable, dictionary-based textual analysis method. As each method has inherent limitations, methodological diversity enables a more comprehensive understanding of VBM (Lachmann et al., 2017).

Second, this is the first study to apply textual analysis to the measurement of VBM sophistication. In doing so, we advance the integration of textual analysis into management accounting research, a field in which such approaches remain at an early stage (Ranta et al., 2023).

Third, our dictionary-based NLP approach may be transferable to other management accounting phenomena. Publicly available data—such as annual reports, conference calls, and social media posts—are particularly suited for studying strategy- and planning-related phenomena such as environmental and social accounting (Guthrie and Abeysekera, 2006), stakeholder communication (Arvidsson, 2023; Fiss and Zajac, 2006), and budgeting (Coyte et al., 2020). In contrast, internal documents—such as minutes, interviews, and internal communications—are more appropriate for studying process- and cost-related practices such as target costing (Woods et al., 2012), or activity-based costing (Malmi, 1997). Finally, other data formats—such as visual, audio, and video data—could provide complementary insights

[19] We employed a robust two-step GMM methodology using the *xtabond2* module in Stata, developed by Roodman (2009a). We used lagged values from periods t-2 to t-4 as instruments for the transformed equation and t-1 for the equation in levels (Roodman, 2009a) and collapsed the instrument matrix to prevent instrument proliferation (Roodman, 2009b). Following prior research, we treated year and industry dummies as exogenous variables and all other independent variables as endogenous (Firk et al., 2016; Fremeth and Shaver, 2014; Uotila et al., 2009). We employed conventional diagnostic tests to assess the specification of the model: Wald χ^2 statistics, Arellano and Bond's (1991) proposed tests for serial correlation (AR(1)) and (AR(2)), and the Hansen over-identification test. All tests indicated an appropriate model specification and valid instruments.

[20] We applied the following adjustment to the VBM sophistication (raw count) variable: First, we computed the lagged ($t - 1$) and lead ($t + 1$) values of the raw VBM sophistication measure for each firm-year observation. Second, we defined a threshold epsilon that indicates unusually large fluctuations. Based on this threshold, we constructed a dummy variable (D_{it}) that takes the value of 1 if the following condition holds:

$\text{VBM(raw count)}_{i,t} > \text{VBM(raw count)}_{i,t-1} + \text{epsilon}$ and $\text{VBM(raw count)}_{it} > \text{VBM(raw count)}_{i,t+1} + \text{epsilon}$

and 0 otherwise. We set the threshold epsilon to seven n-grams, which corresponds to the average year-on-year change in the VBM measure. A firm-year observation was therefore flagged as a temporary spike if its VBM score exceeded both the lagged and lead values by more than seven n-grams. This relatively modest change supports the view that VBM-related communication is consistent within firms over time: firms do not appear to make abrupt or erratic shifts in their VBM orientation. Taken together with our earlier result that 71 % of the variation in VBM usage is explained by firm identity, these findings suggest that VBM sophistication is a moderately persistent, firm-level trait. For these flagged years, we adjusted the VBM score by pulling it closer to the lead year using the following formula:

$\text{VBM\_adjusted}_{it} = \text{VBM (raw count)}_{it} + D_{i,t} \times (\text{VBM (raw count)}_{i,t+1} - \text{VBM (raw count)}_{i,t})$.

This adjustment helps smooth isolated spikes that may reflect temporary disclosure changes rather than substantive shifts in VBM practices.

(Mahlendorf et al., 2023).

Fourth, we assess the construct validity and reliability of the VBM sophistication measure. We contribute to the management accounting literature and address a criticism raised by previous scholars that little attention is paid to construct development and validation (Anderson and Lillis, 2011; Chenhall, 2003; Luft and Shields, 2003). This novel measurement approach contributes to theory building and the development of research programmes as new measures may facilitate the empirical corroboration of theories (Malmi and Granlund, 2009; Modell, 2022).

Fifth, we expand on Qiu et al.'s (2023) emerging and highly promising research on NLP-based measures of management accounting practices by introducing evidence from an international sample of 17 countries, and by examining the performance effects of this NLP-based measure of VBM sophistication.

6.2. Limitations, future research, and conclusion

The limitations of our study also provide avenues for future research. First, similar to other studies, our proposed text-based measure relies on secondary data from annual reports (Firk et al., 2021; Firk et al., 2019b; Knauer et al., 2018). Thus, our proposed VBM sophistication measure assumes that disclosure volume proxies actual VBM sophistication. We cannot completely rule out that firms differ in their styles of reporting on their VBM practices (Firk et al., 2016). However, it would be surprising to find a positive performance effect of VBM if firms were—as we coin it—'*goldwashing*' their annual reports, that is, reporting but not genuinely pursuing VBM practices (Firk et al., 2019c). Given the significant statistical correlation, it is more reasonable to assume that competent investors and analysts can interpret various reporting styles. Moreover, our approach provides a valuable complement to others that facilitate large-scale, longitudinal, and resource-efficient analyses. We agree with Lachmann et al. (2017) that the use of diverse methods is important for gaining a comprehensive understanding of management accounting phenomena. We suggest that future research could provide more insights into the relationship between disclosure and actual practice. Second, the authors' perception and judgement regarding the inclusion or exclusion of n-grams could have biased the compilation of the dictionary, although we took steps to mitigate this possibility by following prior suggestions in developing the dictionary and by performing initial validity tests to alleviate this concern (McKenny et al., 2018; Short et al., 2010). Future research could utilise other approaches such as traditional machine learning (supervised or unsupervised) or deep learning to validate the assumptions of our measure and to reduce author subjectivity. However, these approaches also have their own limitations and run the risk of being less transparent (Lewis and Young, 2019). Since textual analysis is in its infancy in management accounting research (Ranta et al., 2023), we decided to use a simple and easily replicable method that is applicable in the management accounting context. Third, we relied solely on corporate annual reports for the development of our text-based measure. Future research could use other textual data such as investor relations webpages, transcripts of conference calls, or press releases to increase the robustness of such a textual analysis. Alternatively, future scholars could use graphical data such as tables or pictures to extract relevant accounting information (Mahlendorf et al., 2023).

In summary, this paper demonstrates the development of a novel VBM sophistication measure which we apply to explore new theoretical insights. We hope that this paper stimulates further discussions about the use of NLP in management accounting research.

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Declaration of Competing Interest

No.

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Appendix A. Origin and development of the term 'VBM sophistication' in the literature

Wobst et al. (2025) categorise seminal VBM studies by measurement approach: symbolic espousal, binary adoption, or sophistication. They identify 43 studies that empirically measure VBM sophistication using diverse data sources. Our citation analysis of these papers revealed that all of these papers centre around only two *theory-based definitions* of what VBM sophistication is, namely Burkert and Lueg (2013) and Firk et al. (2019c).

Regarding the six most seminal studies of the total 43, Firk et al. (2019c) acknowledge that the first established definition of VBM sophistication originates from Burkert and Lueg (2013). Burkert and Lueg (2013) base their definition on four foundational papers which discuss key concepts underpinning their new *sophistication* term: the 'comprehensiveness' of VBM practices (Malmi and Ikäheimo, 2003), the 'extent' or 'extensiveness' of VBM practices (Fiss and Zajac, 2004; Ittner et al., 2003), and the importance of ensuring both decision-making and control relevance in such systems (Biddle et al., 1997). Firk et al. (2019c) further expand on Burkert and Lueg's (2013) survey-based definition by tailoring it to their archival approach.

Of the remaining 37 studies (Wobst et al., 2025), 21 do not explicitly mention the term *sophistication* (or similar) in relation to VBM (Athanassakos, 2007; Bezemer et al., 2015; Bhimani et al., 2018; Bluhm and Martens, 2009; Bouwens and Van Lent, 2007; Chiwamit et al., 2014; De Aguiar et al., 2014; Duh et al., 2009; Ezzamel et al., 2008; Gates, 2000; Gleadle and Cornelius, 2008; Goutas and Lane, 2009; Haspeslagh et al., 2001; McLaren, 2004; McLaren et al., 2016; Minchington and Francis, 2000; Shin, 2012; Siti-Nabiha and Scapens, 2005; Tripathi et al., 2019; Wallace, 1998; Woods et al., 2012).

Of the remaining 16 studies, Cooper and Petry (Cooper and Petry, 1994) provide an early definition of sophistication of *Shareholder Wealth Maximization* as the *difference* between sophisticated methods (such as using computer simulation) versus unsophisticated (such as using simple payback period). This difference-based definition, however, has received little attention, being adopted by only two other seminal studies in the field (Elgharbawy and Abdel-Kader, 2021; Ryan and Trahan, 1999).

The remaining 13 studies do not provide new theory-based definitions of VBM sophistication, albeit the eventual empirical measurement may vary according to the chosen data source (Brück et al., 2023; Brück et al., 2018; Chiwamit et al., 2017; Dai et al., 2017; Firk et al., 2019a; Firk et al., 2021; Firk et al., 2019b; Knauer et al., 2018; Lueg and Parashiv, 2023; Mavropulo et al., 2021; Milunovich and Tsuei, 1996; Nowotny et al., 2022; Verbeeten and Boons, 2009). With the exception of Knauer et al. (2018), these 13 studies use the term VBM sophistication without offering a definition and tend to cite almost exclusively Burkert and Lueg (2013) and Firk et al. (2019c) – or, depending on their publication date, their predecessors Malmi and Ikäheimo (2003), Ittner et al. (2003), and/or Fiss and Zajac (2004), or none.

In conclusion, the extant literature strongly suggests that the seminal sources of VBM sophistication are Burkert and Lueg (2013) and Firk et al. (2019c).

Appendix B. The use of textual analysis in business research

A growing number of studies in organisational, management, financial accounting, and finance research employ textual analysis that counts ex ante defined words or n-grams in the underlying textual data (Bochkay et al., 2022; Li, 2010; Loughran and McDonald, 2016). For example, organisational studies use textual analysis to measure entrepreneurial orientation (McKenny et al., 2018; Short et al., 2010) and organisational ambidexterity (Uotila et al., 2009). Strategic management scholars apply textual analysis to measure CEO characteristics (Anglin et al., 2018; McClelland et al., 2010) and firms' global mindsets (Belderbos et al., 2017) while financial accounting research measures the sentiment and readability of corporate texts (Davis and Tama-Sweet, 2012; Henry, 2008; Loughran and McDonald, 2016). Such an approach builds on the assumption that the words used in corporate texts reflect a firm's activities and strategies (Belderbos et al., 2017). Generally, scholars advise developing a customised dictionary that represents the underlying phenomenon by combining deductive and an inductive approaches (Short et al., 2010).

A deductively developed dictionary relies on n-grams that appear in theory-based research or conceptual guidelines. An inductively developed dictionary derives n-grams from a corpus of texts in the field (Belderbos et al., 2017): thus, an inductive approach offers advantages in the extraction of n-grams because it ensures that the word combinations actually co-occur in the field (Illia et al., 2014; Pandey and Pandey, 2019). There are different ways of extracting dictionary n-grams inductively. For example, McKenny et al. (2013) generate an inductive word list of commonly used words in their underlying textual sources. K. Li et al. (2021) rely on a word embedding approach, a machine-learning approach that learns the meaning of n-grams from their context (Bochkay et al., 2022). And Pandey and Pandey (2019) extract noun and verb n-grams using NLP applications, computerised techniques for investigating textual data (Liddy, 2001; Pandey and Pandey, 2019). Validating a newly developed measure is a prerequisite before it is usable in subsequent empirical analyses (Bochkay et al., 2022; Short et al., 2010) as validity assessment examines whether a measure reveals the underlying phenomenon accurately (Cronbach, 1971).

Appendix C. Full dictionary

Seed words	N-grams
Capital	allocation of capital, capital allocation, capital charge, capital charges, capital asset pricing model, capm
Cost	cost of capital, cost of debt, cost of equity, equity cost, equity costs, opportunity cost, opportunity costs
Cfroi	cfroi
Eva	eva, economic value,
Income	residual income
Market	market premium
Profit	economic profit
Return	required rate of return, return to shareholders, return to its shareholders, return for the shareholder, shareholder return, shareholder returns
Risk	idiosyncratic risk, idiosyncratic risks, risk free interest rate, risk free rate, risk premium, risk premiums, risk-free interest rate, risk-free rate, systematic risk, systematic risks, unsystematic risk, unsystematic risks
Shareholder/ Value	build added value, build additional value, build long-term shareholder value, build long-term value, build more value, build shareholder value, build significant value, build sustainable shareholder value, build value, building added value, building additional value, building long-term shareholder value, building long-term value, building more value, building shareholder value, building significant value, building sustainable shareholder value, building value, builds added value, builds additional value, builds long-term shareholder value, builds long-term value, builds more value, builds shareholder value, builds significant value, builds sustainable shareholder value, builds value, built added value, built additional value, built long-term shareholder value, built long-term value, built more value, built shareholder value, built significant value, built sustainable shareholder value, built value, create added value, create additional value, create long-term 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(*continued*)

Seed words	N-grams
	term value, growing shareholder value, growing sustainable shareholder value, growing the value, growing value, grows long-term shareholder value, grows long-term value, grows shareholder value, grows sustainable shareholder value, grows the value, grows value, growth in long-term value, growth in shareholder value, increase in long-term value, increase in shareholder value, increase in value, increase long-term shareholder value, increase long-term value, increase shareholder value, increase sustainable shareholder value, increase the value, increase value, increased long-term shareholder value, increased long-term value, increased shareholder value, increased sustainable shareholder value, increased the value, increased value, increases long-term shareholder value, increases long-term value, increases shareholder value, increases sustainable shareholder value, increases the value, increases value, increasing long-term shareholder value, increasing long-term value, increasing shareholder value, increasing sustainable shareholder value, increasing the value, increasing value, maximisation of long-term value, maximisation of shareholder value, maximisation of value, maximise long-term shareholder value, maximise long-term value, maximise shareholder value, maximise sustainable shareholder value, maximise the value, maximise value, maximised long-term shareholder value, maximised long-term value, maximised shareholder value, maximised sustainable shareholder value, maximised the value, maximised value, maximises long-term shareholder value, maximises long-term value, maximises shareholder value, maximises sustainable shareholder value, maximises the value, maximises value, maximising long-term shareholder value, maximising long-term value, maximising shareholder value, maximising sustainable shareholder value, maximising value, maximization of long-term value, maximization of shareholder value, maximization of value, maximize long-term shareholder value, maximize long-term value, maximize shareholder value, maximize sustainable shareholder value, maximize the value, maximize value, maximized long-term shareholder value, maximized long-term value, maximized shareholder value, maximized sustainable shareholder value, maximized the value, maximized value, maximizes long-term shareholder value, maximizes long-term value, maximizes shareholder value, maximizes sustainable shareholder value, maximizes the value, maximizes value, maximizing long-term shareholder value, maximizing long-term value, maximizing shareholder value, maximizing sustainable shareholder value, maximizing value, protect long-term shareholder value, protect long-term value, protect shareholder value, protect sustainable shareholder value, protect the value, protect value, protected long-term shareholder value, protected long-term value, protected shareholder value, protected sustainable shareholder value, protected the value, protected value, protecting long-term shareholder value, protecting long-term value, protecting shareholder value, protecting sustainable shareholder value, protecting the value, protecting value, protection of long-term value, protection of shareholder value, protection of value, protects long-term shareholder value, protects long-term value, protects shareholder value, protects sustainable shareholder value, protects the value, protects value, value based management, value building, value created, value creating, value creation, value creator, value delivered, value delivering, value delivery, value driven, value driver, value drivers, value enhanced, value enhancement, value enhancing, value for the shareholder, value generated, value generating, value generation, value growing, value growth, value increase, value increased, value increasing, value is built, value is created, value is delivered, value is generated, value is maximised, value is maximized, value management, value maximisation, value maximised, value maximising, value maximization, value maximized, value maximizing, value protected, value protecting, value protection, value was built, value was created, value was delivered, value was generated, value was maximised, value was maximized, value-based management, value-building, value-created, value-creating, value-delivered, value-delivering, value-driven, value-enhanced, value-enhancing, value-generated, value-generating, value-growing, value-increase, value-increased, value-increasing, value-maximised, value-maximising, value-maximized, value-maximizing, value-protected, value-protecting
Wacc	wacc

Data availability

Data will be made available on request.

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