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AI-powered information and Big Data: current regulations and ways forward in IFRS reporting

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Abstract

Purpose – With the help of "self-learning" algorithms and high computing power, companies are transforming Big Data into artificial intelligence (AI)-powered information and gaining economic benefits. AI-powered information and Big Data (simply data henceforth) have quickly become some of the most important strategic resources in the global economy. However, their value is not (yet) formally recognized in financial statements, which leads to a growing gap between book and market values and thus limited decision usefulness of the underlying financial statements. The objective of this paper is to identify ways in which the value of data can be reported to improve decision usefulness.

Design/methodology/approach – Based on the authors' experience as both long-term practitioners and theoretical accounting scholars, the authors conceptualize and draw up a potential data value chain and show the transformation from raw Big Data to business-relevant AI-powered information during its process.

Findings – Analyzing current International Financial Reporting Standards (IFRS) regulations and their applicability, the authors show that current regulations are insufficient to provide useful information on the value of data. Following this, the authors propose a Framework for AI-powered Information and Big Data (FAIIBD) Reporting. This framework also provides insights on the (good) governance of data with the purpose of increasing decision usefulness and connecting to existing frameworks even further. In the conclusion, the authors raise questions concerning this framework that may be worthy of discussion in the scholarly community.

Research limitations/implications – Scholars and practitioners alike are invited to follow up on the conceptual framework from many perspectives.

Practical implications – The framework can serve as a guide towards a better understanding of how to recognize and report AI-powered information and by that (a) limit the valuation gap between book and market value and (b) enhance decision usefulness of financial reporting.

Originality/value – This article proposes a conceptual framework in IFRS to regulators to better deal with the value of AI-powered information and improve the good governance of (Big)data.

Keywords IFRS, AI, Big Data, Intangible assets

Paper type Research paper

1. Introduction

The recognition of intangible assets, such as *data*, has been a much-discussed problem in accounting, and this is not only a problem of the digital age (Aboody and Lev, 1998; Moxter, 1979). Due to the technological change driven by information and communication technologies,

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which have led to the swift digitalization of business models, the importance of the intangible resource "*data*" has increased rapidly. However, the current financial reporting may not be sufficient to recognize the value of this important driver (Lev, 2019; Pei and Vasarhelyi, 2020).

For this reason, a widening gap between the market and the book value of an entity has been seen over the last decade. One major factor in explaining this increasing gap is the intangible assets, mainly those which are not recognized on the balance sheet (Barker and Teixeira, 2018; Gu and Lev, 2017; Haji and Ghazali, 2018), such as *data*. To further demonstrate the relevance of this gap, according to the annual study by Ocean Tomo LLC (2022), intangible resources are already responsible for 90% of the S&P500 market value as of the year 2020. Entities collect and generate huge amounts of various forms of *data* from different sources (called "Big Data"; Bumblauskas *et al.*, 2017; Faroukhi *et al.*, 2020; Wamba *et al.*, 2015) during their normal business operations, and they make use of it by analyzing *data* with sophisticated algorithms and the help of high computing power, to gain information for better decision making (Bhimani and Willcocks, 2014; Cockcroft and Russell, 2018). This smart combination of Big Data, algorithms, and computing-speed power is often dubbed as "machine learning" (Ding *et al.*, 2020), or more broadly as "Artificial Intelligence" (AI) (Greenman, 2017), as human cognition is mimicked by these processes (Losbichler and Lehner, 2021).

Undoubtedly, information gained from Big Data increases the value of companies (Dean, 2014) regardless of its origins (Bhimani and Willcocks, 2014), and the question remains why this is not yet well reflected in financial statements (Lev, 2019). Providing financial information means supplying decision-usefulness information for the users of financial statements (for example Hitz, 2007; International Accounting Standards Board [IASB], 2018). Users might expect a holistic picture. This primary objective of accounting is more important than ever in an increasingly digitalized economy, as discussed previously (Warren *et al.*, 2015). Therefore, it should be of great interest for management, shareholders, and potential investors to know the value of any *data* existing within the entity. According to Atkinson and McGaughey (2006), a statement of financial position that excludes major assets is misleading, and is of little to no use if it does not provide a holistic picture.

Although the objective of the International Financial Reporting Standards (IFRS) is to provide users of financial statements with decision-useful information, not all intangible assets (especially internally generated *data*) of an entity are recognized in the balance sheet; and even if they are, the value shown is significantly below the potential (future) economic benefit (Barker and Teixeira, 2018), which results in the above-mentioned growing gap between book and market value. Especially as the use of internally generated *data* can be seen increasingly as a strategic economic resource that influences current and future cash flows, it is highly misleading to exclude internally generated *data* from the statement of financial position (balance sheet).

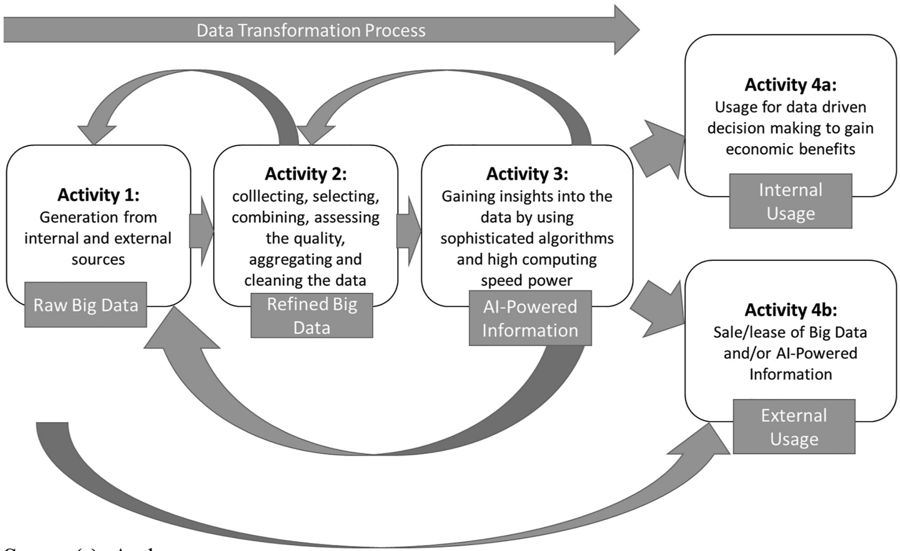
In the last few years, accounting literature has dealt with the question of how Big Data impacts the tasks, roles, and activities in accounting (Bhimani and Willcocks, 2014; Cockcroft and Russell, 2018; Leitner-Hanetseder *et al.*, 2021; Vasarhelyi *et al.*, 2015; Warren *et al.*, 2015), how it might improve financial decision making, or how financial reporting might take place (Warren *et al.*, 2015). However, there is little research on factors that deals with *how to recognize* and even less on *how to assess* the increasingly important (potential) value of *data* within financial statements (Birch *et al.*, 2021; Warren *et al.*, 2015; Schwarz, 2020; Xiong *et al.*, 2022). May this be true to the fact that *data* recognition and *data* assessment may need new, innovative and out-of-the-box research initiatives in the age of digitalization (Monteiro *et al.*, 2020) as *data* are seemingly totally different from the previous assets recognized under IFRS? *Data* are intangible, non-financial, generated with little or no money, and multipliable at any time; it also brings with it the possibility of gaining huge cash flows in the future. The question thus remains, even more problematically, do we still lack an understanding of the economic resource "*data*"?

Admittedly, there are parallels to existing assets already recognized under IFRS, but currently, no single existing standard (such as IAS 38 Intangible assets) offers the possibility to recognize the full (future) economic potential of *data* (especially internally generated *data*). This paper, therefore, deals with the questions of whether the existing IFRS standards contain initial indications that would enable us to recognize and assess *data*, and whether there are other prospects, such as off-balance sheet accounting, for reporting the value of data in a separate statement or disclosure, with the necessity of a separate board focusing on *data* reporting. The fact that IFRS reporting is a dynamic process is also reflected in the current efforts of the IFRS Foundation to establish an International Sustainability Standards Board (ISSB), which in turn will set IFRS sustainability standards to ensure global consistency, reduce complexity in sustainability reporting, and also achieve adequate governance (IFRS Foundation, 2021a).

This paper is structured as follows. First, in section 2, we introduce the *data* value chain to improve our understanding of the economic resource "*data*," especially the transformation from Big Data to AI-powered information. In section 3, we discuss ways to recognize and assess the economic benefit of *data* within financial statements, given the current IFRS regulations. Finally, in section 4, we suggest a framework for a separate statement of the valuation of (good) governance of *data*, to provide information that has decision usefulness and conclude with future research questions that would help us develop it further.

2. The transformation from Big Data to AI-powered information within the *data* value chain

In order to understand the "value chain" of *data* in companies, we describe how *raw* Big Data are transformed into information by the use of sophisticated algorithms (henceforth "AI-powered information") (Bhimani and Willcocks, 2014; Cheng *et al.*, 2002; Choi and Chung, 2002; Wang *et al.*, 2020), and how the *data* can be used to generate competitive advantage and value (Cockcroft and Russell, 2018; Warren *et al.*, 2015), as shown in the following Figure 1. Although the term "Big Data" is ubiquitous, a strong definition of the term itself does not exist (Bumblauskas *et al.*, 2017; Ward and Barker, 2013), and the naming is often based on certain characteristics that are often ambiguous. Big Data are undoubtedly associated with huge *data* sets requiring advanced *data* storage and retrieval facilities and is comprised of structured (clearly defined *data* type and meaning) as well as unstructured *data* (e.g. texts with varying lengths, missing context) (Brinch *et al.*, 2018; Faroukhi *et al.*, 2020). Big Data might be generated by various internal and external sources, such as macroeconomic data or social media data, or obtained from internal sources (Faroukhi *et al.*, 2020; Schwarz, 2020; Vasarhelyi *et al.*, 2015). Such internal sources could include Enterprise Resource Planning (ERP) Systems, human interactions (verbal and non-verbal), mobile devices usage, or data automatically generated by the internet of Things (IoT) machines and devices (Chartered Professional Accountants of Canada; Vasarhelyi *et al.*, 2015). According to Wamba *et al.* (2015), "Big Data" are characterized by the 5 Vs: volume, variety, velocity, veracity, and value. However, Big Data do not create value *per se*. Value is not only generated by simply recording, collecting, and (potentially) selling *data*, but also by obtaining insights through a process called data analytics; this involves sophisticated algorithms and sheer computing speed to aggregate, summarize, and visualize data into information that is accessible to humans for decision making (Janvrin and Watson, 2017; Warren *et al.*, 2015). There are many examples (i.e. predictive analytics, risk evaluations, audit assurance, digital twins) of how such a transformation process can create a competitive advantage which enables economic benefits from the available *raw* Big Data (Cockcroft and Russell, 2018; Griffin and Wright, 2015; Wamba *et al.*, 2015).



Source(s): Authors

Figure 1.
Data value chain: data transformation process and the two perspectives of data usage

In the following text, an imaginary "data value chain," analogous to Porter's value chain (Porter, 2001) is described, to help us identify inputs and interactions, which can create competitive advantage and value from Big Data. In detail, the *data* value chain is a model that identifies data as *raw* Big Data that is transformed into a distinctive commodity by the above-mentioned AI-powered processes (Faroukhi *et al.*, 2020), leading to business-relevant information and therefore to a competitive advantage. The data value chain thus includes the transformation process from Big Data to AI-powered information, and finally to the business use of this *data* to create an economic benefit for the entity (Chen *et al.*, 2015). The difference between this process and other value chains, such as manufacturing, is that the final result is useful insights rather than a tangible product or a service.

In addition, we also identify activities relevant in the data value chain. This accords with Porter's statement that "*value activities are the building blocks of competitive advantage*" (Porter, 2001). According to Porter (2001), there is always an interaction between activities; even if the value chain can be seen as a system of independent activities, the activities are nevertheless interconnected and these connections may lead to a competitive advantage through expert coordination and overall optimization. Having a look at the data value chain, the first activity is to generate Big Data. As mentioned previously, Big Data can be produced by various internal sources and devices, but of course it can also stem from an external provider, accessible either for free (e.g. publicly available data) or bought. To make use of the generated data, it is necessary to select and transform the data. Therefore, the second activity starts with collecting the right data for the specific purpose (Vasarhelyi *et al.*, 2015). According to Faroukhi *et al.* (2020), this includes selecting and combining the appropriate sources and assessing the quality of the data, as well as aggregating and cleaning the data (see also Cross-Industry Standard Process for Data mining (CRISP-DM); Chapman *et al.*, 2000). In the third activity, the preselected, cleaned, and aggregated data are analyzed with AI technology (sophisticated algorithms with high computing speed) to identify patterns and trends which might be relevant for managerial purposes or for external use by customers and partners (Faroukhi *et al.*, 2020). This results in smart, extracted information (Faroukhi *et al.*, 2020; Mockenhaupt, 2021). The goal is thus to provide AI-powered information that allows data-based decision-making (Bhimani and Willcocks, 2014), which might be of value for internal or external partners.

This conversion of Big Data into AI-powered information requires economic resources such as IT infrastructure (for example, a database management system (DBMS)) (Schwarz, 2020); data analytics tools (such as KNIME, Tableau, Power-BI); AI technology; and most importantly, employees who have the know-how to ask the right questions and apply the right algorithms to transform Big Data into information. However, the transformation process from Big Data to AI-Powered Information cannot be understood as a linear one; rather, it can be assumed that it will need to be an agile process that requires repeated and iterated adjustments to the *data*. It can also be assumed that additional data are constantly being generated and contains possible new information, and thus needs to be revisited on a regular basis. Activities 1 to 3 are, therefore interrelated, but also show an inflow of constant feedback. This may lead to the refinement of the algorithm: for example, in deep-state neuronal networks (NN) (Ashley and Empson, 2016; Ding *et al.*, 2020), which learn from each additional information to make better decisions and predictions. A practical example of this may be cloud-based accounting applications with a neuronal network core. With every customer and case (e.g. a new invoice), the amount of data and possible extracted information increases, and the NN core learns from the additional examples. After a while, prediction and interpretation of the cases will be very accurate, and thus the value of the software would be much higher for customers and for the company, as the NN core has learned from each case and thus gained more experience. It can thus be said that in some cases, value will be created not only by the data but also in combination with algorithms such as NN and would perhaps need to be seen and recognized in combination. This is also corroborated by technical and cognitive perspectives, as scholarly literature agrees that Big Data in its scope is beyond human cognition (Duan *et al.*, 2019; Losbichler and Lehner, 2021), and thus needs to be processed and evaluated by sophisticated machine learning (Ashley and Empson, 2016; Ding *et al.*, 2020) in order to prepare and visualize AI-powered information (Perkhofer *et al.*, 2019). This is, of course, not to say that Big Data in itself cannot have value, as it can, for example, be sold to external partners.

Chen *et al.* (2015) noted that as long as an entity cannot make use of Big Data, value is not created. Chen *et al.* (2015) further defined Big Data's utility only in terms of gaining organizational competitive advantage. However, we see two opportunities to make use of the *data*: through internal and external usage. Internal usage corresponds to gaining a competitive advantage by employing the *data*, for example, by gaining better insights into business processes, thereby supporting complex, data-driven decision-making (Green *et al.*, 2018; LaValle *et al.*, 2011). Competitiveness and economic benefits are therefore enhanced, for example, through the reduction of costs or errors by setting optimal prices, or by further clarifying customer needs (Anshari *et al.*, 2019; Krahel and Titera, 2015; Lee, 2017). External usage means that *data* might be sold or left for usage by external partners (Faroukhi *et al.*, 2020). In this external perspective, raw Big Data, as well as AI-powered information, creates economic benefit through revenues and cash flows from the sale or lease. In the fourth and logical last activity in our data value chain, *data* are used by internal (activity 4a) or external partners (activity 4b) in a way that generates an economic benefit.

In some cases, the same *data* generates revenue from both internal and external usage. An innovative and recent example of this is the so-called "digital twins" (Cuc, 2021; Golovina *et al.*, 2020; Miehe *et al.*, 2021). A digital twin (DT henceforth) can be seen as a virtual model of physical objects, processes, and/or whole systems (He *et al.*, 2018). Creating this virtual model requires enormous computing power, sensors that permanently generate data (sometimes via so-called "edge devices"), sophisticated algorithms, and physics-based computing frameworks. This combination is used to create and continuously update a dynamic virtual model of the physical object (Grieves, 2014; Huang *et al.*, 2020; Park *et al.*, 2020), and can be used to simulate and identify important patterns. The DT can thus be seen as AI-powered information that allows vendors and customers to simulate and customize the physical object in the virtual world. Through this, companies can vastly reduce process and production costs. For example, vendors can demonstrate complex products in virtual showrooms to allow for easy and cost-effective customization, leading to a more *personalized* production mode (Liu *et al.*, 2019). At the same time, data generated by the customers could be collected on the vendor's platform in order to further improve the DT (Tao and Qi, 2019). Learning from the data obtained will enhance not only the simulation but also the future physical products and help to optimize maintenance schedules. Furthermore, in addition to the physical product, the DT might even be sold/leased to customers to optimize their own production processes (Huang *et al.*, 2020). Clearly, a DT increases competitiveness and brings economic benefits via its internal and external usage scenarios.

With the data value chain in mind, we can now proceed to discuss the potential recognition of the economic resource *data* with regard to its *internal and external usage* under IFRS.

3. Recognition of data and AI-powered information in IFRS financial statements

3.1 Does the conceptual Framework (2018) provide a chance to recognize data and AI-powered information as an asset?

The purpose of IFRS financial statements is to provide financial information that is useful for existing and potential stakeholders' decision making, and they should be able to assess the entity's economic resources (CF par. 1.2 et seq.). The above-mentioned increasing gap of listed companies' book versus market value was also already targeted by the Conceptual Framework 2018 (CF) of the IASB, which became effective on or after January 1, 2020. This CF targets the gap and deals in principle with the recognition of assets, more specifically with internally generated, intangible assets (with the exception of goodwill) (Barker and Teixeira, 2018). In this framework, a first step to close the gap is the redefinition of the term "economic resource," whereby "*an economic resource is a right that has the potential to produce economic benefits*" (CF par. 4.2). Unlike the 2010 Framework, in which it was necessary to provide *probable* economic benefits, CF 2018 requires only *potential* economic benefits. This implies a lower requirement for the recognition criteria and might increase the likelihood of recognizing *data* as an asset in earlier stages. This is particularly helpful in our discussion, as we pointed out previously that *data* might only provide economic benefits after reaching a certain threshold (either over time or in combination with various data sources), where it becomes Big Data, and may then have been processed enough by sophisticated algorithms to provide AI-powered information. Due to the lower requirement of recognition, we see that *data* might meet the criteria of an economic resource. However, "probable" and "potential" are undefined legal terms with the CF, which allow room for interpretation and ambiguity (Schwarz, 2020).

Furthermore, CF par. 1.14 sees that some of the resources may generate future cash flows only in combination and thus create an *economic benefit* for the entity. This can be seen as analogous to our description in section 2, in which we outlined how the transformation of Big Data into an economic benefit requires a combination of resources (e.g. human resources; computing equipment; and sophisticated, self-learning, deep-state algorithms). This is another indication that AI-powered information might meet the criteria of an economic resource under CF, and perhaps AI-powered information as a unit of account might even be defined by the economic benefit-generating *combination of data and algorithms*, in a continuous dynamic and iterative process cycle. Thus, the importance of clearly defining what comprises the "unit of account" seems crucial for any way forward. A standard definition of what makes a unit of account reads: "*is the right or the group of rights, the obligation or the group of obligations, or the group of rights and obligations, to which* *recognition criteria and measurement concepts are applied*" (CF par. 4.48); or, according to Barker and Teixeira (2018), "*the thing being accounted for.*"

The next question that arises is whether the resource of Big Data or AI-powered information can be recognized as an asset. An asset under CF 2018 is "*a present economic resource controlled by the entity as a result of a past event.*" Control implies "*the present ability to direct the use of the economic resource and obtain the economic benefits that may flow from it*" (CF par. 4.2). This of course also implies that the entity needs to take the necessary precautions to ensure the persistence of its control, for example through data protection and security measures. Indeed, leaked data would be publicly available (loss of control) and might no longer even generate an economic benefit. Referring back to the data value chain, an entity directs AI-powered information for external or internal usage; this leads to obtaining economic benefits and thus follows the definition of a controlled economic resource. Therefore, we suggest that AI-powered information meets the criteria of an asset under CF 2018 if this is the case. Additionally, contrary to the Framework of 2010, further facilitation of asset recognition can be seen in CF 2018, which does not require a reliable estimation of the value *a priori*.

We, therefore, postulate that these two innovations – the change in wording of *probable* to *potential*, and the removal of the reliable *a priori* value estimation requirement in CF 2018 – could further assist the recognition of data under IFRS. Thus, in cases when the economic benefit is not probable but potentially possible, and the measurement of its value is also not yet reliable (Schwarz, 2020), AI-powered information or Big Data alone may be recognized. Nevertheless, the low probability of an economic benefit, and the lack of reliability in its value estimation, will certainly affect recognition and assessment of the asset (KPMG, 2020).

However, despite these promising prospects, it is clear that the CF 2018 provides only general guiding principles for IFRS financial accounting, such as the definition of an asset; and it assists preparers of financial statements when *no* specific IFRS Standard applies to a particular transaction or event, but it never overrides any specific IFRS standard. This means that in the case of a conflict between CF 2018 and the specific IFRS standard, the standard is to be given preference and predominates over the CF (CF 2018; SP1.2).

3.2 Do specific IFRS standards allow the recognition of Big Data and AI-powered information?

Therefore, we need to refer to the specific IFRS standards. AI-powered information and Big Data "*that are held for sale in the ordinary course of business; in the process for such production for such sale; or in the form of materials or supplies to be consumed in the production process or in the rendering of services*" are classified for "external usage" (see section 2) and are seen as inventories according to IAS 2 which are recognized as an asset.

However, if the requirements of IAS 2 are not met, the question arises of whether data meets the definition of an intangible asset under IAS 38. As data do not meet the criteria of a monetary asset and is without physical substance, it meets the definition of an intangible asset (IAS 38 par. 8). Additionally, the definition of intangible assets requires that the intangible asset is identifiable and controlled by the entity (IAS 38 par. 11 et seq.) Identifiability is based on the idea that the intangible asset is either separable, which means that *data* are being separated from the entity and sold, transferred, licensed, or exchanged; or arising from contractual or other legal rights (IAS 38 par. 12). Indefinability makes it possible to separate intangible assets from goodwill (IAS 38 par. 11). To control intangible assets means that "*the entity has the power to obtain the future economic benefits" (IAS 38 par 13)* and "*to restrict the access to others to those benefits*" (IAS 38 par. 13). In general, *data* will fulfill the two criteria: identifiability and control. To prevent others from accessing the data, blockchain technology, as a "new notary" may be used to ensure actual ownership.

This includes so called smart contracts being embedded and run on the blockchain for the due and transparent transfer of ownership/control. This means that the control of the data can be guaranteed by legal rights in accordance with IAS 38 par 13. However, the two required criteria (identifiability and control) will not be fulfilled in any case. For illustrative purposes, we provide relevant examples where *data* does not meet the definition of an intangible asset under IAS 38. For example, if AI-powered information represents distributed "self-learning" algorithms (multi-agent systems) whose functionality is not specified *a priori* (Werner, 2017) and whose traceability is also not guaranteed, not the "self-learning" algorithm itself, but only the unit of account "AI-powered information," might fulfill the criteria of "identifiable" and "controlled by the entity". Another example goes hand in hand with the conclusion of the IFRS Interpretations Committee, 2011 that a contract that merely grants the customer the right to access the provider's application, running on a cloud infrastructure and therefore lack of control, is not an intangible asset under IAS 38, or a lease under IFRS 16. It can be concluded that Big Data or self-learning algorithms provided by the supplier on a cloud infrastructure are also not to be understood as intangible assets (Hanke, 2020).

In addition, and contrary to the revisions in the CF 2018 as discussed above, recognizing an intangible asset according to IAS 38 requires that the entity that identifies and controls the intangible assets expect a "*probable*" future economic benefit from it, and that the cost can be measured reliably (IAS 38 par. 21). However, even if a probable economic benefit is expected, but the *data* are not measured reliably, then the data are not recognized as an intangible asset. For *data* which is acquired in a business combination or in a single acquisition, the criteria of probable economic benefits and reliable measurement are met (IAS 38 par. 25, 26 and 33).

For internally generated *data*, it is the entity's responsibility to prove that the additional criteria under 38 par. 57 et seq. are met, which are essentially a concretization of the criteria for probable future economic benefit, as well as reliable measurement and require the separation into a planning phase, a research and development phase, and a use phase. All costs incurred in the planning and research phases must be recognized as an expense in accordance with IAS 38 par 54. Only the costs of the development phase are to be capitalized (IAS 38 par. 57). IAS 38 is currently based on a linear project progression for development projects. This is also reflected in IAS 38 par. 53, which declares that if it is not possible to distinguish the research phase from the development phase, all the costs must be expensed. Furthermore, costs incurred after use and commissioning are considered as only for the purpose of preserving future economic benefits, and are recognized as maintenance expenses in profit or loss. In practice, activities to create an intangible asset might not be so easily distinguished and classified into either research or development (KPMG, 2020) and usage. Such sequential processes, based on old, linear thinking, will hardly have any significance for *data* in an agile business world (Hoeren and Pinelli, 2018). As shown in the data value chain, AI-powered information might be in a constant state of change, as new data will constantly refine and update itself with the help of self-learning, deep-state AI-powered algorithms; this will lead to a constant shifting between the planning, research and development, and usage phases. This will make a clear separation of the phases impossible, and thus interfere with the necessary decisions regarding costs, and which ones can be recognized. But even if we can assume that we are able to capture the costs during the development phase, do the costs incurred until use really reflect the economic benefit of *data*? Comparatively low costs for data storage and the often automated in-process generation of the individual data bring low costs of the "raw material". Furthermore, IAS 38 par. 71 excludes the capitalization of costs already expensed in the planning or research phase. Therefore, the capitalized development costs might be quite low, and certainly do not reflect the (future) inflow of economic benefits. Thus, the cost model would still account for the huge book-market value gap that we have identified previously. Therefore, the question arises of whether current measurement regulations are able to close the book–market value gap.

3.3 Does the current assessment reflect the (future) economic benefit?

In this section we focus on the assessment of AI-powered information or Big Data, with the aim of assessing *data* appropriately regarding (future) economic benefit. Intangible assets under IFRS are in general initially recognized at cost (IAS 38 par. 24). Only, if *data* are acquired in a business combination, the cost of the data are the fair value at the acquisition date (IAS 38 par. 33), which can be seen as "*a one-off estimate of cost*"" (Nobes, 2015).

In the case of internally generated *data*, the assessment would require accounting for all the costs necessary for generation, collection, and refinement of *data* and analyses. The costs of conversion of *data* include costs directly related to the unit of account, such as direct labor for collecting, refining, and analyzing the data; as well as fixed and variable production overheads incurred during the transformation of raw Big Data into finished AI-powered information. Therefore, it is necessary to provide a reliable cost accounting, to recognize, classify, allocate and report the costs of data conversion. Summing up, depending on the way control over the AI-powered information or Big Data are obtained, the probability of the expected economic benefits differs.

Therefore, *data* that is internally generated or acquired separately is initially measured at cost. However, if the fair value of the asset can be measured by reference to an active market at a subsequent measurement date, the revaluation model is applied from that date (IAS 36 par. 84). This requires subsequent measurement to assess the *data* at fair value, and that an increase or decrease should be recognized through other comprehensive income. Nevertheless, according to the experience of Nobes (2015), and as mentioned in IAS 38 par. 78: "[. . . *It is uncommon for an active market to exist for an intangible asset* . . .]". In addition, even if AI-powered information or Big Data are sold, these are in general a unique asset, and according to IAS 38 par. 78 "*the price paid* [. . .] *may not provide sufficient evidence for the fair value of another*." Therefore, even if IAS 38 par. 78 offers the possibility, the requirement of an active market (with high frequency and transaction volumes, and low bid-ask spreads) (IFRS 13) will make it impossible to assess *data* at fair value. This may change, however, as we see the onset of several *data* market platforms that will increasingly generate an active market in the future.

Additionally, if the same data set or AI-powered information is acquired in a business combination, assessment at fair value is required, even if the asset is still unique and not actively traded. Moreover, unlike IAS 38, IAS 41 requires biological assets to be measured at fair value less costs, to sell at the point of harvest, and argues that this is because the transformation process of the biological asset requires fair value measurement (Barker and Teixeira, 2018). The question is whether fair value measurement is transferable to the transformation process of *data*, and if not, why?

As in IAS 41 par. 32, this reflects the view that the fair value or the value in use can be assessed reliably. However, the proposals for measurement may contradict the prudence principle required by the CF 2018. Therefore, we suggest a recognition comparable to that of contingent assets, following IAS 37 par. 31 et seq. A contingent asset that is not virtually certain is not recognized in the financial statement but disclosed in the notes. For the recognition of data or AI-powered information, we propose that when an economic benefit is not probable but possible, the economic benefit should be disclosed in the notes. However, when the economic benefit of the data or AI-powered information is probable (see IAS 37 par. 33), the recognition of the data as an asset is appropriate. Since off-balance sheet recognition might be a possible way forward, we explore this idea in the next section.

4. Off-balance sheet recognition: a solution to recognize the economic benefit of data

As mentioned, the purpose of IFRS financial statements is to provide financial information that is useful for existing and potential stakeholders' decision making and should be able to assess the entity's economic resources. This does not necessarily require that self-generated AI-powered information and Big Data (*data*) have to be recognized as an asset within the balance sheet – which, as we have elaborated in the previous sections, might not be fully achievable at present. However, the balance sheet is only one reporting element, and in order to assess the benefit of an economic resource, there are other possibilities, such as supplementing the notes, or even a separate statement. A comparable need for an off-balance sheet recognition has already been highlighted recently in the realm of sustainability (Adams and Abhayawansa, 2021; Sætra, 2021; Tóth *et al.*, 2021).

In order to avoid a lack of comparability from the beginning, which has been criticized in the context of sustainability reporting (Cardoni *et al.*, 2019; Silva Lokuwaduge and Heenetigala, 2017), we propose working on a single, integrated framework for AI-powered information and Big Data reporting that covers the whole data value chain, as described in the previous sections, and leads to a well-defined statement. This differs from earlier approaches on the reporting of strategic resources, such as from Lev and Gu (2016), who proposed including five topics: resource development, strategic resources, resource preservation, resources deployment, and value created. Nevertheless, this framework effort supports the International Integrated Reporting Committee (2013) in their quest to provide deeper insights on value creation in financial reporting. As this might lead to dilution and superficiality, we suggest concentrating on reporting one strategic resource only. To further support an automated content analysis in this report, we also suggest the establishment of a machine-readable format such as iXBRL from the beginning, which includes detailed tagging advice (for example, in the ESEF (Beerbaum *et al.*, 2019)) or even i/u-XBRL that provides customized internal and external data (Pei and Vasarhelyi, 2020).

From our point of view the decision usefulness for shareholders will be a major focus of any resulting statement. From our point of view, however, our proposed framework for a statement of AI-powered Information and Big Data Reporting (FAIIBD Reporting henceforth) should consider an investor's point of view but also embrace the perspectives of the stakeholders because of the societal dimension (and potential impact) of AI and Big Data. In addition, besides reporting the value, it also needs to include information concerning the (good) governance of *data* (see Figure 2). This can be done based on the existing COBIT framework (Bernard, 2012), with specific adaptions according to the nature of AI-powered information (duality of data and algorithms).

First, derived from our in-depth explanation in the previous sections, we propose that in order to show the value of *data*, it is necessary to first differentiate between the *purpose* of the data and actual *usage* (internal and/or external). Following the above-identified activities in the data value chain, we then see the need to distinguish between *raw* and *refined* Big Data, as well as AI-powered information, to enable the individual measuring and reporting of the *data* in terms of its

(1) exact nature (including structure and type)

(2) source (including data quality, reliability, and exhaustibility)

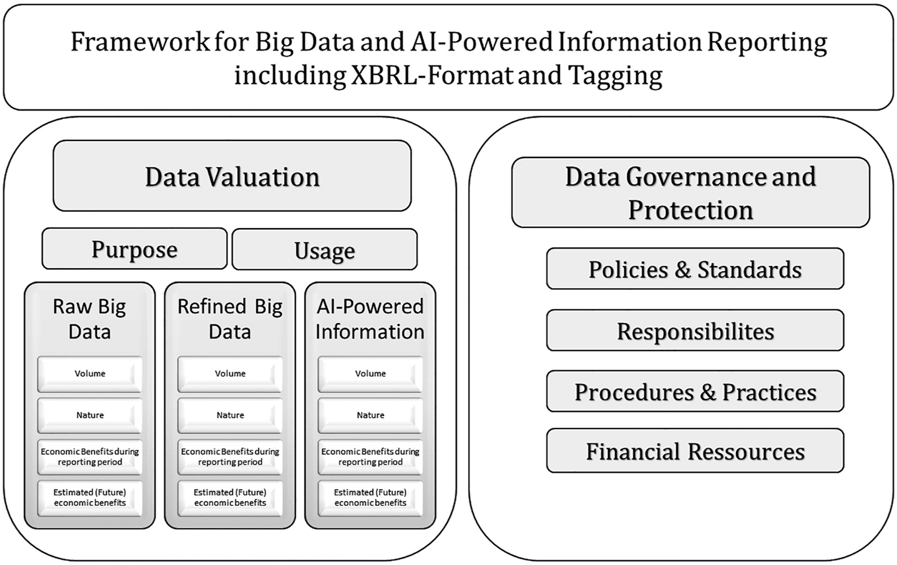
(3) unit of account, especially within the context of the dyadic structure of *data* and necessary algorithms

(4) property, legal rights and obligations, as well as applicable norms

(5) volume and capacity utilization

(6) accumulated achieved economic benefits per period

(7) estimated, discounted future economic benefits, and



Source(s): Authors

Figure 2.
Framework for the statement of AI-powered information and big data reporting (FAIIBD Reporting)

(8) data-specific risk assessment (including operational, reputational, market, and legal risks)

Comparable to IT governance and frameworks such as COBIT (Bernard, 2012), the aim of the *data* governance is to develop a strategy that is part of the corporate strategic planning process and ensures that the data are managed and protected as a strategic resource which creates value (Pei and Vasarhelyi, 2020), and that financial resources are allocated to it. This protection plays an essential role in ensuring (future) economic benefits: for example, through investments in reliable storage technologies, but also through securing legal rights and investing in human resources to ensure a proper knowledge base. Governing data also includes the risk assessment throughout the value chain (International Integrated Reporting Committee, 2013; Pei and Vasarhelyi, 2020) and a managed balance of risks and rewards. Data governance reporting should include policies and standards, responsibilities, procedures and practices; as well as financial resources to set direction, monitor value, mitigate risk, and ensure data protection and security in all activities of data generation, refinement, storage, and use.

With regard to these topics, changes compared to previous periods are of particular interest in order to be able to assess sustainable development.

The resulting statement based on the FAIIBD would thus allow users to gain granular insights into the data value chain and would allow automated aggregation because of its structure and machine readability. Furthermore, it would increase the transparency of data governance, including protection and risk assessments.

Similar to the sustainability reporting considerations proposed by the IASB in an exposure draft this year, we would therefore suggest the creation of a new board focusing on the topic “AI-powered Information and Big Data (FAIIBDA) Reporting.” The members of this board would need to carefully collect expert know-how in this area and strive for global consistency in the application of the proposed framework and standards. While it certainly seems ambitious to create another board, it is nevertheless timely and apt, as digitalization can be seen as the second major driver for businesses in the next decades, besides the necessary sustainability focus. Furthermore, as the new taxonomy of sustainability reporting demands adequate assurance, which can only be achieved by making use of advanced AI-powered algorithms in audit to deal with the vast, qualitative, textual information; many synergies in the reporting of both sustainability and data will arise. It is thus inevitable that the future will see a strongly linked triangle of synergies between financial, sustainability, and data reporting. The connection between these three areas of reporting within IFRS can be made by using the IFRS Practise Statement 1 Management Commentary, with the related Exposure Draft having been issued in 2021. The aim of this Management Commentary is to complement the information of the financial statements and to provide further insights into facts that might impact an entity's value or future cash flows from an investor's point of view (IFRS Foundation, 2021b). This goes in line with the current considerations in sustainability reporting, whereby an entity is required to disclose sustainability-related information as part of the general purpose financial reporting (IFRS Foundation, 2022). Therefore including sustainability and data reporting in the Management Commentary could be a chance to link financial, sustainability and data reporting.

5. Conclusion

This article set out to provide useful information in an era of the increasing importance of AI-powered information and Big Data (we coined the combination "*data*"), to create value through (future) economic benefits. To achieve this, we first examined the *data value chain* and concluded that *data* provide economic benefits via improved decision-making (internal usage) and economic advantages gained, as well as through direct returns/flows from selling/leasing data to external users. Additionally, we used different aspects and perspectives to establish that current IFRS regulations are insufficient for reporting and determining the (fair) value of *data*. As the gap between market and book values continuously widens and more and more businesses are embracing "digital" business models based on clever combinations of algorithms, Big Data, and alternative, innovative, and open ways of organizing (Baum and Haveman, 2020), we believe that these accounting shortcomings need to be addressed in order to help make better decisions and be ready for a digital future.

As a step forward, we propose a framework leading to a separate statement (AI-powered Information Reporting and Big Data (FAIIBD) Reporting) that brings insights into the value of *data* created along the data value chain and further provides information about (good) data governance. Additionally, to better align this framework with existing regulations and to provide globally accepted standards, we suggest the establishment of a new board dealing with the topic of *data* and its governance, similar to current developments in the area of sustainability reporting.

Based on our proposed early framework, much work now needs to be done in order to make it practicable and aligned with the existing standards. The following non-exhaustive list contains some first questions that need to be dealt with in the near future:

(1) Who needs to report (a statement's breadth and scope)?

(2) How do we need to refine the exact structure of the statement?

(3) What comprises the true nature of "Big Data" and "AI-powered information" in their combination and in relation to algorithms and deep-state neural networks in detail?

(4) What might be the unit of account for the dyadic structure of *data* and necessary algorithms for AI-powered information?

(5) How to measure the quality and quantity of various types and forms of *data*?

(6) How to measure and report the accumulated achieved economic benefits per period?

(7) How to measure and discount the estimated (future) economic benefits (discount rates, time horizon, and flows)?

(8) Which data-specific risk assessment, including operational risks and also reputational, market, and legal risks, is necessary, and how does it overlap with existing risk considerations?

(9) What might be a definition of materiality of the information reported?

(10) Which standards are required to inform about (good) governance?

(11) What would an efficient and effective assurance of this statement look like, and what would be the role of expert auditors in this?

To conclude, we strongly believe that a statement of AI-powered Information and Big Data (FAIIBD) would increase the decision usefulness of financial reports in times of increasingly data-driven business models, and we invite the scholarly community, practitioners, and regulators alike to help us further refine the proposed framework and assist in addressing the above questions.

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