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The Big Data, Artificial Intelligence, and Blockchain in True Cost Accounting for Energy Transition in Europe

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Abstract: The current energy prices do not include the environmental, social, and economic short and long-term external effects. There is a gap in the literature on the decision-making model for the energy transition. True Cost Accounting (TCA) is an accounting management model supporting the decision-making process. This study investigates the challenges and explores how big data, AI, or blockchain could ease the TCA calculation and indirectly contribute to the transition towards more sustainable energy production. The research question addressed is: How can IT help TCA applications in the energy sector in Europe? The study uses qualitative interpretive methodology and is performed in the Netherlands, Germany, and Poland. The findings indicate the technical feasibilities of a big data infrastructure to cope with TCA challenges. The study contributes to the literature by identifying the challenges in TCA application for energy production, showing the readiness potential for big data, AI, and blockchain to tackle them, revealing the need for cooperation between accounting and technical disciplines to enable the energy transition.

Keywords: True Cost Accounting; big data; sustainability; blockchain; AI; energy production

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1. Introduction

The energy markets face challenges in the transformation towards sustainable alternatives, with some European countries such as Sweden and the Netherlands showing stronger readiness than others, i.e., Poland and Hungary [1–3]. The technical and social aspects of energy production in transitioning towards renewable alternatives seem extensively covered in literature [4–7]. From the economic perspective, there are business models for classification [8] and accounting frameworks introduced to track the energy efficiency trends [9]. There is a gap, however, in the literature on the decision-making model for the energy transition. Specifically, studies are scares on how to enable decision-makers throughout the energy production chain (from energy sources and production entities to energy (pro)consumers) to make better decisions, i.e., choose more sustainable alternatives. This paper addresses this gap by analysing the True Cost Accounting model for energy cost estimation based on a broad scope of information covering all aspects of the energy production chain, both internal and external. The analysis goes beyond a single discipline and combines technical and accounting literature to critically assess the TCA model for energy cost estimation. Further, it explores the potential of an innovative idea of strengthening the TCA model with big data, Artificial Intelligence, and blockchain. In doing so, it contributes to developing a new body of literature on big data use in the accounting field. The study investigates the transition challenges facing the energy sector and explores how the use of big data, AI, or blockchain could ease the TCA calculation and indirectly support the

move towards more sustainable operations. The primary research question guiding this study is how IT can help TCA applications in the energy sector in Europe. In answering this question, we investigate the current challenges of TCA and the current use of big data in management accounting.

Big data, AI, and blockchain, as elements of Industry 4.0, show different levels of development across countries in the European Union [10,11]. The current study applies a multidisciplinary and multinational approach to collect opinions from a diverse group of relevant stakeholders—IT specialists, sustainability and energy experts, and accountants—in the European energy market, with particular focus on the Netherlands, Germany, and Poland, and the countries with contrasting energy markets, levels of industry 4.0 advancement, and development of the accounting discipline.

1.1. Literature Review

True Cost Accounting Framework

TCA is a management accounting concept that estimates a true cost [12,13]. TCA is a holistic approach accounting for current and future, internal and external impacts, by discounting it in a single price [12,14,15]. TCA provides insight into the complex economic, social, and ecological processes through which sustainability should be attained [16]. As a result of the TCA application, the existing prices of products and services can be adjusted to include the internal and external impacts throughout the whole lifecycle of the products or services [17]. Consequently, sustainable decision making may be stimulated by putting a price on otherwise seemingly free impact costs to society [13]. The stimulation can enable the energy markets playing an important role in tackling the climate change [10,18], making the externalities of energy production visible which are hardly included in the cost estimations [11,19].

The TCA framework consists of five steps as shown in Figure 1 [20]. The first four steps are essential for calculating the cost, the fifth step consider management decisions made after the estimation and will be omitted in the current study.

1. Analyse company situation and map stakeholders engaged. Identify a cost object by analysing the company situation [20]. A cost object refers to a process, a waste stream, an industry, or an entity. Based on the cost object, a True Cost price calculation will be performed.
2. Define the cost object to identify and outline the scope of the impacts: here, all the possible externalities (side-effects/by-products or unintended production results) should be identified. It is essential to set the limit on how far to go. Externalities can be endless, so a well-defined scope is required.
3. Measure all impacts within the scope of the cost object [20]. Life cycle assessment (LCA) analyses are helpful since they specify the full usages of materials and the waste streams created.
4. Monetise all the significant impacts into a monetary unit [20]. This helps overcome comparison and integration issues for social and environmental impacts [21,22].

Literature on TCA reveals several challenges in its application. For example, the measurement and monetisation methods are incomplete, and TCA requires development to provide complete and comprehensive coverage of all the identified impact categories [17]. Furthermore, TCA is complex and should therefore provide useful information efficiently in order to improve its applicability for practice [17]. This effectivity–efficiency tradeoff is important since the costs of the analysis should not outweigh the benefits of more useful accounting information. When analysing the challenges of TCA, three categories are identified: complexity, accuracy, and timeliness.

Figure 1. True Cost Accounting framework. Source: [20].

1.2. TCA Challenges

1.2.1. TCA Complexity

1. Society, the environment, and the economy are interrelated elements interacting with each other. TCA deals with the different scales and domains of social, environmental, and economic impacts and those impacts are interrelated. Measurements not integrated into one single and comparable unit [23] have consequences for interpreting the result.
2. Across industries and throughout the life cycle of a product, different metrics are used for measurement and monetisation [17]. There is no consensus on measurement and monetisation, and this lack of standardisation makes it difficult to measure the product's impacts uniformly [23]. Especially with regard to monetisation, many different valuation methods exist [24,25].
3. TCA uses data from multiple disciplines, such as bioscience, biology, psychology, economy, and accounting, to understand the interaction among organisations, society, and the natural environment [26]. Each new practice for measurement and monetisation creates a new focus for negotiation, contestation, and political struggle over values [27].

1.2.2. TCA Accuracy

1. Some impacts deal with emotions and subjectivity, for example, landscape or stress, and are difficult to quantify and assign value [28].

Monetisation uses different valuation methods: direct behavioural and indirect valuation [17]. The first technique measures the monetary value directly from the preferences or behaviour of the stakeholder and uses available market prices and observed actual behaviour [17]. The accuracy challenge occurs in all situations where differences appear between what stakeholders say 'they would do' and what 'they actually do' [17]. The indirect techniques estimate either cost of avoidance and restoration or damage costs [17]. The avoidance and the restoration approaches use real market prices for existing technological solutions to avoid, restore, or control pollution or damage. The damage costs approach estimates the damage caused by a pollutant using scientific, statistical, and behavioural valuation methods [17]. All the approaches mentioned above share shortcomings in the

availability of the data and the reliability of the price estimates, causing inaccuracies in this step.

2. The true cost of an impact depends on its context and the interlinkages of variables. Takin the water usage on its own, for instance, is an incomplete measure to capture the true cost of the water usage (water use in areas with plentiful rainfall is less stressful than the water used for milk and cattle grazing) [23].

1.2.3. TCA Timeliness

1. Long-term cost estimation is characterized by different time lags and inertia, which masks those important cause–effect relations when captured at one point in time [26]. For example, one ton of extra CO^2 emission now will lead to more expenditures for tackling climate change in the future. However, it is difficult to determine now how aggressively the climate will warm up in the upcoming years and what those expenditures will be in the future. Many variables determine the true cost of an impact [29], and these become fully visible only in the long run.
2. The time lag in the measurement and the monetising of the impact are uncertain [30]. It takes some time to gain insight into those processes or for the information to reach managers [31]. When the accounting impact information reaches the user, a problem may arise that the accounting information has become outdated [31].

1.2.4. IT and TCA

The current study proposes to address the challenges in TCA application, using IT as the primary data source for account management [32]. Generally, IT systems can collect, organize, process, and distribute large amounts of data [33], allowing accountants to interpret data from many sources [34]. IT systems can be defined as a set of interrelated components, such as software, hardware, people, procedures, and data that collect, process, store, and distribute information to support decision making and organisational control [35]. IT systems have shifted from traditional data processing to more progressive and automated data capture, and consequently, more variety of unstructured data sources such as big data can be exploited [36]. Accounting methods integrate with this new reality of big data [37]. AI is an outcome of a successful application of big data that can help understand the past and predict the future based on a large amount of data [38]. It prevents information overload, predicts future events, and analyses voice-based data and images and other data sources that are currently not being used in accounting [38]. In addition, blockchain may be useful in accounting. Blockchain is described as a series of blocks used to establish and record the ownership of assets, in which an arbiter is not required [39,40]. This enables the direct exchange of accurate financial information and improves the efficiency and reliability of transactions [41] and the integrity of transaction history.

Table 1 shows the literature overview on big data applications in accounting, including several trials data mining applications are prominent within management accounting [42].

1.2.5. TCA Big Data in Coping with Complexity

Big data and AI enhance the processes of data collection, identification of cause and effect relations, integration of data, translation of raw data into meaningful information, and the representation of the data on a manageable and accessible scale more efficiently [65]. Automating the processes of identifying cost drivers, forecasting future costs, measuring impacts, and evaluating impact in a monetary unit may increase efficiency. Descriptive and predictive data mining helps identify cause–effect relations in the database, allocating impact costs to certain activities and estimating future costs. Moreover, to reduce the complexity, it is important to reduce the scope of TCA. Within big data analytics, it is important to determine the goal of the analysis [66]. A clear question enables the designer of the big data tool to exclude all but the relevant data. Therefore, big data and AI may reduce TCA's complexity and consequently enhance the TCA's potential application. Blockchain may also reduce the complexity of TCA since it supports the automated exchange of

relevant data by all involved parties accurately and efficiently [67]. Moreover, blockchain uses predefined protocols for a uniform sharing of information, and this standardisation of data sharing may further reduce the complexity of TCA.

Table 1. Data mining applications within accounting literature.

Application of Data Mining Studies in Management Accounting	Brief Description of the Research
Esmat et al. (2018)	Data mining was used to predict customer demand
Wald et al. (2013)	Data mining was used to allocate costs to activities more efficiently
Hämäläinen and Inkinen (2017)	Data mining was used to reduce emission costs
Chou et al. (2011)	Data mining was used for the estimating equipment manufacturing costs
Chou and Tsai (2012)	Data mining was used to improve the accuracy of equipment inspection and repair in cost management
Dessureault and Benito (2012)	Data mining was used for tracing equipment replacement costs
Kostakis et al. (2008); Liu et al. (2012)	Data mining was used in defining drivers in activity-based costs and improving production routing
Yu et al. (2006); Shi and Li (2008); Miglaccio et al. (2011); Vouk et al. (2011)	Data mining was used to construct cost management, create neural network systems for a faster and more accurate estimation of the total unit cost of construction, and for operation and maintenance
Chang et al. (2012)	Data mining was used to forecast product unit cost
Yeh and Deng (2012)	Data mining was used to estimate product life cycle cost
Deng and Yeh (2010); Deng and Yeh (2011)	Data mining was used to estimate project design and product manufacturing costs
Petroutsatou (2012); Kaluzny et al. (2011)	Data mining was used to develop a project-level cost–control system
Chen and He (2012)	Data mining was used to develop a project level cost–estimate system
Yu (2011)	Data mining was used to develop ABC classification techniques
Xing et al. (2015)	Data mining was used to evaluate and predict educational performance
Zhou et al. (2015)	Data mining was used to predict financial distress

Source: [43–64].

Proposition 1. *Big Data, AI, and blockchain reduce the complexity of TCA practices.*

1.2.6. TCA Big Data in Coping with Accuracy

Big data, AI, and blockchain may improve the accuracy of TCA, particularly its measurement and monetisation steps. Here, data mining may be useful. Data mining, defined as the process of identifying valid, potentially novel, and understandable patterns in data [68], allows for the identification of causal relations and better forecasting of future costs. Data mining is the most important current paradigm of advanced intelligent business analytics and decision-supporting tools [42]. In data mining, specific algorithms are used to extract patterns from data with three different goals: description, prediction, and prescription [42]. Descriptive data mining refers to understanding and interpretation of the data. Predictive data mining analyzes the past to predict the future by detecting patterns of behaviour and extrapolating future actions based on those patterns [42]. Prescriptive data mining refers to achieving the best possible outcome. So far, within management accounting, the prediction function has been used the most often since estimation is the most common task in managerial accounting application of data mining [42]. AI uses data mining tools to build logic behind the data to forecast future outcomes and identify patterns for allocating impacts to activities [45]. In order to arrive at the true cost estimations, the interplay between discounting, uncertainty, damages, and risk aversion is important to consider [29]. Those four elements can be integrated into a formula, and consequently, the true cost can be estimated. Accounting may help determine the need and formula to extract

value from the data [69]. Insight should be provided in what data is needed and what relevant variables capture the problem, based on which an analytic model can be built [42].

Consequently, analytics tools can translate the raw data into valuable decision-making knowledge [70]. Blockchain is a distributed digital ledger used to record and share information through the peer-to-peer network [71]. Identical copies of the ledger are validated collectively by all network members [72]. This technology implies that, due to the decentralisation feature of blockchain, it is impossible to alter information in a block at a single location. This results in efficient, secure, transparent, and accurate processing [72]. Thus, blockchain in TCA may enable linking measurement data from the production line to the monetisation for environmental, social, and economic impacts accurately and efficiently. Consequently, it allows the sharing of TCA measurement data between all the involved parties within the value chain. Together, blockchain, big data, and AI may help identify the cause–effect relations within the data, support forecasting of future costs, and accurately share the measurement data.

Proposition 2. *Big data, AI, and blockchain result in more accurate TCA applications.*

1.2.7. TCA Big Data in Coping with Timeliness

Digitalisation allows accounting information to be produced, distributed, and interpreted in real time [73]. Different databases connected to each other provide, via automated censoring, real-time insight into the TCA. The measurement of the impacts identified in the lifecycle of a product, or a service, can be linked directly to the monetisation of the external and internal costs resulting in a real-time true cost price. The environmental, social, and economic external data can be integrated with the internal database of production and automatically updated [45]. The analytical tools will identify relations and correlations and allocate impact costs to production processes. Big data enables open-source information sharing so that all involved parties within the life cycle provide and use the required real-time data to perform the TCA analysis. Blockchain allows for automated exchange and verification of information, measurement data between parties in the whole value chain can be directly shared [67]. For TCA, that is advantageous since, in order for TCA to work, the required data should come from measurement for which consensus is required by the involved stakeholders. Blockchain, furthermore, allows the secured exchange of that data between all the parties without the approval of an arbiter [67]. This improves the real-time accounting of information and thus the real-time awareness regarding sustainability.

Proposition 3. *Big data, AI, and blockchain application results in timelier TCA information.*

Figure 2 presents the conceptual model for the study and summarises the propositions.

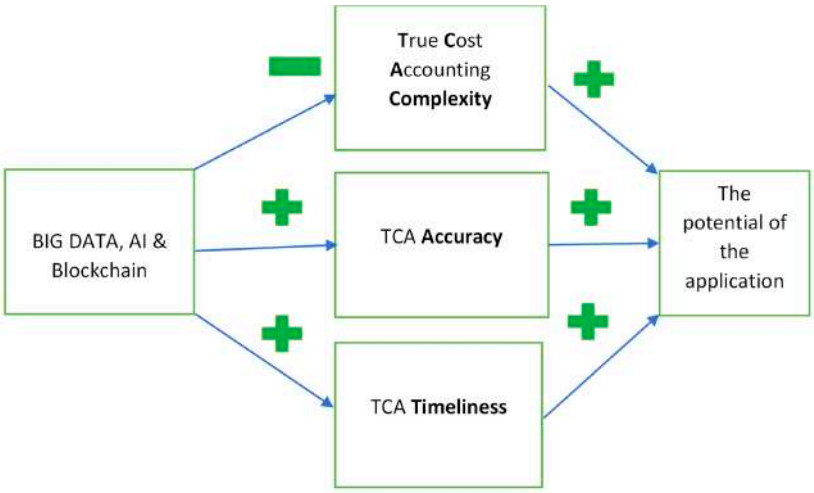

Figure 2. Conceptual model. Source: own study.

2. Materials and Methods

This research aims to contribute to the literature on sustainability accounting by providing insights into improving the TCA methodology with the application of big data, AI, and Blockchain. The task requires an exploratory research design and interpretive research to explore the reasons and dynamics behind the complex, interrelated processes [74]. The concept of sustainability accounting is complex and draws together many academic disciplines. Therefore, the potential application of IT technologies and their influence on the TCA application could only be explored within their social context [74]. Using a qualitative approach to understand the processes behind the TCA method can provide meaningful insight into how to improve its methodology [75]. Inductive reasoning was used, as there was no theory at the start of the research, and any theories that were developed are a result of this research [76].

2.1. Constructs

The selection of impacts used in the True Cost Accounting exercise used in the current study is shown in Table A1 in the Appendix A. In preparation for this study, the TCA application and estimate of the true price of energy production showed a high complexity of the exercise and low accuracy and timeliness. The complexity, accuracy, and timeliness were the core concepts guiding the current study. The accuracy referred to the degree to which relevant estimates were reliable, the degree to which cause and effect chains between activities and impacts could be identified, the degree to which subjectivity and uncertainty could be reduced in estimating costs, and the degree to which the measurements provided detailed and reliable data. Complexity was operationalized as the degree to which different metrics were required to measure environmental, social, and economic impacts, the degree to which the TCA analysis was costly and time consuming, the degree to which different academic disciplines were needed in the analysis and the degree to which they diverged, the degree to which different monetisation methods were required and the degree to which different dimensions and attributes of data sources could be brought together into one scale. Timeliness relates to the degree of accounting data processing in real time, the degree to which the data were available and to which measurement from the production could be directly linked to the monetisation assessments.

In order to discuss the application of big data, AI, and blockchain, the different types of energy production costs were discussed with each respondent to discern the types of costs IT allowed to arrive at more accurate, timelier, and less complex TCA estimation. The scoping was limited to the material impacts, meaning that the plant and system costs have been identified as internal costs. Greenhouse gas emission costs, air pollution costs, landscape and noise impacts, loss of biodiversity, and upstream costs of material and construction have been identified as the external costs for the energy market [25].

The true cost estimation trial for wind and coal energy in the Netherlands conducted prior to this research showed that construct is defined fractionally, and selected impacts are included in the energy cost due to the shortcomings in data availability and processing ability. In an attempt to identify a complete scale of material impacts, several were identified and monetized, as shown in Table 2.

2.2. Data Collection and Respondents

The data were collected in a cross-sectional manner and consisted of interviewing the experts on how impacts of energy production can be measurable and translated into meaningful data. The current study used an earlier developed stakeholder map for the Dutch energy market of Bosma [25]. The respondents were selected based on their expertise in big data, analytical software, and accounting tools to provide insights on how big data applications might help TCA processes. Similarly, Galliers and Huang [77] used experts to provide alternative narratives to the dominant paradigm. The expert panel provides a forum where leading experts in a given field can share their experiences and insights [78].

Table 2. True Cost Accounting estimate for wind and coal energy.

Cost price of Energy Generation in EUR/kWh.	Onshore Wind	Offshore Wind	Hard Coal	Coal with CCS after Combustion
Installation costs	4.4	7.6	1.5	7.0
O&M costs	1.0	2.0	0.8	1.0
Fuel costs	0.0	0.0	2.0	2.0
Sum of plant-level costs (a)	5.4	9.6	4.3	10.0
Grid costs	1.0	1.0	0.5	0.5
Balancing costs	0.3	0.3	0.0	0.0
Profile costs	1.5	1.5	0.0	0.0
Sum of system costs (b)	2.8	2.8	0.5	0.5
GHG emissions costs	0.1	0.09	7.11	2.34
Air pollution costs	0.07	0.07	1.37	1.47
Landscape and noise impacts	0.9	0.08	<0.1	<0.1
Loss on biodiversity	Data not available		0.2	0.3
Employment benefits	(<0.01)	(<0.01)	(<0.01)	(<0.01)
Upstream costs of materials and construction	0.45	0.45	1.9	1.9
Cost of nonrecyclable materials	0.0000015	0.0000015	<0.0000015	<0.0000015
Sum of all quantifiable external costs (c)	1.53	0.7	10.6	5.6
Sum of all quantifiable costs (a+b+c)	9.73	13.1	15.4	16.1
Year	2019 S1	2019 S2	2020 S1	2020 S2
Energy market prices in the Netherlands EUR /kWh (Statista, 2021)	20.52	20.55	14.27	13.61
Market prices energy in Germany (Statista, 2021)	30.88	28.78	30.43	30.06
Market prices energy in Poland (Statista, 2021)	13.43	13.76	14.75	15.71

Source: own calculations.

The same (Dutch) proxy of the stakeholders was used for Polish and German energy markets due to the time constraints and since the system complexity of energy generation was treated as similar across the EU countries.

The more variety exists in the data, the more patterns, relationships, and knowledge can be extracted [79]. The Netherlands, Poland, and Germany energy markets were selected for the study. Poland and the Netherlands are among the least sustainable European energy markets [80] but show contrasting trends in industry 4.0 developments; the Netherlands is one of the most advanced, Poland the least [10,11]. Germany, in contrast, is currently reducing the amount of CO^2 emissions significantly and is on the way to becoming the pioneer in renewable energy [81]. In total, 16 respondents were interviewed (see Appendix B, Table A2) with a total interview time of almost 22 h. The interviews were conducted via Google Meet due to COVID-19 restrictions on location in the summer of 2021. Before the interview, a document containing the stakeholders' analysis, an overview of the types of energy production costs, an infographic presenting the environmental and societal impacts of energy production, and the true cost calculation for the Dutch energy market preparation study were shared with the respondents [25]. Consequently, these documents were discussed with the experts to introduce them to the concept of TCA. The interview guide was used as a baseline for the interview questions (see Appendix C). The interviews were recorded to improve the data analysis process, and the transcripts were sent to the respondents for verification purposes.

2.3. Data Analysis Method

In preparation for this study, the true cost estimation outcomes (Table 2) were discussed with the representatives of coal (RWE) and wind energy-producing companies. The current study used an interpretative and thematic data analysis approach. The interviews were divided into three themes: accuracy, timeliness, and complexity. Consequently, the interview transcripts were coded according to the three themes. Quotes from the interviews are placed in tables in the results section (and also appear in the narrative itself). The

narratives were created following Gray [82]. Gray states that narratives are needed to provide alternative insights and move the boundaries of TCA [82]. Narratives are used to enrich the current literature on TCA and provide insights into overcoming the current challenges. Based on the quotes from the respondents, the researcher attempted to assess the degree to which IT can make the TCA methodology more accurate, timely and less complex, making use of the coding software but leaving much space to diverse opinions and trying to grasp the richness of information.

3. Results

In general, in Europe, the energy prices do not cover the external influences of energy production [83]. The estimations made during the preparation for this research were new to most of the respondents and were received with much interest. Presenting Table 2 to the respondents certainly contributed to broadening awareness of the externalities issue and revealed the lack of applicable and common methodologies. According to the wind farm owners we interviewed in Poland, there are no reliable procedures for this influence. Further, they mentioned that the cost of avoiding negative impacts should be accounted for in the investment planning stage. Owners are aware of potential external influences of production. The owner shared the information that during the service of the wind farm, the service technicians found that there was a bird's nest with eggs in the high gondola of the power plant. The owner believed that this is little evidence that the production of energy from this source does not pose a radical threat to the birds. A wind power plant is also a wintering place for ladybugs and other insects. The wind farm became part of the natural environment. The coal energy plant controller in the Netherlands mentioned a similar situation. Including the external effects during the investment, phase is essential as then is easier to make a change rather than when the energy production takes place already. However, the obstacle mentioned was missing the procedures and techniques to make it visible and account for it.

Further results are presented according to the constructs described in the literature review part. During the first interviews, a new aspect appeared to challenge the respondents, namely TCA implementation. It was added in the following interviews and reported in the results, as it kept coming back.

Overall, the level of awareness about TCA was more advanced in the Netherlands than in Poland, in the last country where the interviewer faced difficulties in bringing the concept of TCA into the discussion. Moreover, in Germany and the Netherlands, relative openness and transparency were experienced while it was to a lesser extent present in Poland.

3.1. Complexity

The results of complexity experiences could be divided into five areas: metrics, cause and effect relationships, diversity of experts needed to collaborate, number of indicators, resource consumption. Table 3 shows the challenges and solutions developed from the results.

To summarise, big data and AI allow for the automation of data collection and management in TCA, resulting in a decrease in the complexity of TCA processes. The tools are becoming cheaper and are available in identifying patterns, forecasting costs, and allocating costs to drivers. This shows support for Proposition 1.

3.2. Accuracy

The accuracy of TCA estimations is a challenge in five areas: quantification and monetisation, fluctuation, objectivity, data availability and ethics. All respondents mentioned the importance of having a good base—input for interpretation. (. . .) We first have to make sure that the basis is good before we let big data and artificial intelligence let loose on it. (. . .) R10. Table 4 provides an overview of the most important findings on accuracy deficiencies and potential solutions.

Table 3. TCA complexity and solutions.

Result	Challenge	Solution	Result
(. . .) thousands of indicators that all interrelate (. . .) R10	Large number of interrelated indicators	Technology is available. Data can be stored in data centres; AI used to detect patterns, blockchain secures	(. . .) having large amounts of data is crucial for the evaluation of the whole situation (. . .) R3 (. . .) The technologies are already there. (. . .) R4, R11
(. . .) we compared 30 to 40 different metrics (. . .) R2	Common standard	AI detects patterns can serve as standard development	(. . .) we have a lot of artificial intelligence that can detect patterns very well, and we can visualize data very nicely (. . .) R4, R11
(. . .) It is hard to consider the whole chain in the life cycle since something can have almost no impact in the direct environment, but a huge impact elsewhere (. . .) R4 (. . .) You have to be an expert in all areas. Everything comes together in such a study (. . .) R7	Cooperation throughout the life cycle /supply chain	Sharing data would potentially ease cooperation. Blockchain would	No direct support in the data found; data sharing is an issue.
(. . .) In order to comprehend something like biodiversity loss, it is difficult to see how a population develops, and that is cost-intensive (. . .) R3 (. . .) These all are sub-topics that are all in-depth and time-consuming (. . .) R5	Manual data collection is costly due to human resource and time consumption	Sensors connected to a blockchain system	(. . .) sensing is becoming cheaper and cheaper (. . .) R2 (. . .) Automated cost systems process a large amount in a short time. (. . .) R3

Source: own study.

Table 4. TCA accuracy and solutions.

Result TCA	Challenge	Solution	Result IT
(. . .) In many cases, there are impacts that cannot be expressed in CO_2 equivalents. (. . .) life expectancy, child mortality and human development index are typically things that are not really monetary (. . .) R7	Uncertain estimations	AI modelling	(. . .) Technically, you can model each little step of it, and I think you can come up with pretty precise models (. . .) R2
(. . .) Impacts can occur in 10 years or 100 years, so there is always an uncertainty range here. (. . .) R5 (. . .) This gives a lot of data problems since data is often not available (. . .) R6	Data unavailable	Data mining	(. . .) I believe this information is not available in real time. I use this information ex post. (. . .) R16
(. . .) It is difficult to predict future climate change policies and whether or not countries will stick to the climate agreements. A value, therefore, is never definite, and it is constantly subject to changes (. . .) R5	Fluctuating values	Identifying relationships through AI modelling	(. . .) If you caught those parts in a well-defined causal relation with triggers and conditions, then a computer is able to forecast (. . .) R4
(. . .) If data is collected manually, they have a low credibility (. . .) R11–13 (. . .) Everything is built on assumptions and proxies (. . .) R5 (. . .) Currently, there is a great deal of subjectivity in assessing externalities, biodiversity, etc. R16	subjective character	Objectivity inherent in the blockchain	(. . .) Blockchain is perfect for getting verifiable data. Given ten different categories of costs, you also have ten different protocols and foundations that verify those numbers. (. . .) R9 (. . .) If everyone uses the same protocol, data can be exchanged uniformly and verified (. . .) R9
(. . .) I haven't seen those social values on your list yet. But if you leave it out, you take the heart out of the system. So, my advice is put them in (..) R10	Ethical quantification of social impacts	Data streams to develop definitions	(. . .) data streams and the democratisation of data, i.e., making this data available allows socially to simplify and show the effects of an action: that something good or bad (. . .) R11–13

Source: own study.

At last, ethical consideration is important as well. Social values, such as equality, the right to live a worthy life, and freedom are currently included in the TCA estimation in the descriptive elements. The IT application would allow for pattern recognition and quantification at a later stage.

To summarise, the IT technologies enable objective identification of patterns and forecasting future costs technically possible. Further, blockchain allows for exchanging verifiable and hygienical data, which improves TCA accuracy. The results show support for Proposition 2.

3.3. Timeliness

The availability of real-time data in TCA is essential to be able to communicate the holistic aspect of sustainability. If some data is available later, then the estimation of true cost isfragmented. Currently, due to the manual data collection at each step of TCA, a time-lag is created by the process itself. Table 5 presents the solutions to the challenges for the timeliness aspect.

Table 5. TCA timeliness and solutions.

Result TCA	Challenge	Solution	Result IT
(. . .) data from 2014 and here is a study from 2016 and together you arrive at this number (. . .) R9	Time lag in TCA process	IoT sensors and data mining models including immediate processing	(. . .) The IoT devices that we have, and sensing that we have, absolutely allow to get real-time measurements (. . .) R2 (. . .) The input data can be measured in real time via sensors and IoT devices. I do not believe that the human can use it directly. So, you need an immediate processing (. . .) R2
(. . .) It does depend on what is being measured. For example, CO_2 emissions and nitrogen are already being measured in real time. (. . .) R5	Time lag in data availability		
(. . .) I believe that aggregate data influences long-term decisions, i.e., investments. Real data is needed, e.g., when the level of pollution is close to the maximum, harmful to people, then we should be able to make decisions and take action fast, to change the source. (. . .) R16	Data in different metrics appear in different timeframes	Standardisation of data models	(. . .) You can report on it, in a calculation model, in every time frame window or even live, provided that you have standardized it. That is really important here (. . .) R4, R11
(. . .) I wonder how much the data collected here and now delivers to us versus the data aggregated after a quarter or half a year or a year. I believe that aggregate data influences long-term decisions, i.e., investments. (. . .) R16			(. . .) Here, the analysis in the real state makes sense, certain things at the level of companies can be arranged and optimized in this way (. . .) R16

Source: own study.

Here, the received solutions show a mixed picture. The costs of providing real-time insight may not outweigh the benefits of real-time information; therefore, the real-time data available should be explored further.

(. . .) The adding of all new details may not be necessary. It may be better to update the whole analysis once in a while instead of real time. The cost and benefit consideration are important here (. . .) R7.

To summarise, the tools and technologies currently available allow for improving the timeliness of TCA information to some extent showing partial support for Proposition 3. Clearly, no information needs to be available in real time at all costs. Some delays can potentially strengthen the results.

3.4. Implementation

The implementation of the TCA technique in general and specifically with support of IT in combination with big data, AI, or blockchain kept running into obstacles. Currently, the human aspect of collaboration between parties to arrive at reliable and comprehensive true cost estimation seems to be the biggest challenge. Institutions seem to be working independently of each other lacking collaboration and developing too many methods not accepted by the industry. The results suggest that adopting an open blockchain would eliminate the need for collaboration, therefore, solving this challenge instantly.

Ownership of data is an issue in the implementation. Companies are hesitant to share sensitive information. Blockchain and automation may deal with these issues around data ownership and other parties looking into the sensitive data.

(. . .) Companies are probably only willing to share their data, preferably by AI in an automated manner (. . .) R9.

(. . .) The first attempts have been taken to make an open protocol to enable uniform and congruent sharing of data (. . .) R9.

The main challenge concerning the application of blockchain technology in TCA is gaining mutual consensus on working in one platform.

(. . .) The whole circular chain of events in the lifecycle of energy production should be united in the blockchain. That means that you will need to combine different blockchains since you can never have just one blockchain. So that may become complex exercise (. . .) R4.

4. Discussion

The early stage of adopting True Cost accounting to include the externalities is due to a lack of awareness of what they are and what they constitute. We find the results repeatedly in The Netherlands, Germany, and Poland. In all three countries initiated by us, the open discussion about the challenges to estimate the true cost of energy prediction, including the externalities on economic, social, and environmental dimensions, was received with ingenious interest. Participants engaged in the TCA exercise agreed on the importance and the value of this approach in decision-making on the transition to sustainable energy prediction. When presented with opportunities for improving the TCA estimation with the aid of IT, specifically big data, AI, and blockchain, many opportunities emerged, most of them supporting the Propositions developed in the literature review.

4.1. Complexity

The results support Proposition 1, which means that big data technology enables search for patterns and cost drivers to predict and allocate costs to activities in a more efficient manner also by developing standards. Big data application allows dealing with the TCA's information overload and time consumption challenges. Individuals cannot comprehend that complexity, and therefore automation of TCA using big data technology seems highly promising. Currently available IT technologies are advanced enough to deal with massive amounts of data sets to find patterns. The combination of TCA and big data is, therefore, value adding. More variables can be included in the analysis, and consequently, the system can be analyzed as a whole instead of as isolated elements of the system. Literature on management accounting already acknowledges the potential of big data for accounting [84] in general. The current study adds to the literature showing the potential of big data for such advanced management accounting as TCA, which requires combining financial and nonfinancial data from interdisciplinary resources.

Although big data implementation in TCA has not yet started, the application of big data and AI may accelerate the TCA development by reducing or even eliminating TCA complexity.

4.2. Accuracy

The results show support for Proposition 2. This indicates that the application of IT reduces the negative challenges of TCA concerning the accuracy of measurement and monetisation.

Therefore, installing a big data environment and consequently statistically modelling afterwards enable precise quantifications and valuation, improving the cost allocation and reducing uncertainty in predicting future costs. Technically, everything is possible.

The problem is that all involved parties should cooperate to help install the data environment This cooperation is weak or absent at the moment. A government may step in here to steer the industry or mandate information measuring and sharing using blockchains. It may have no interest to do so or fear the change in that applying blockchain would allow for the perfect exchange and continuous verification and sharing of TCA data. The application of blockchain technology would enable sharing of data without manipulation. If happening, the uncertainties within the parameters will permanently cease to exist. It is impossible to precisely predict what will happen in the future, and a complete story of causality in the system is challenging. In the meantime, TCA may use standard risk management accounting techniques, e.g., Groot and Selto discuss the risk in decision making [85]. Some types of costs in energy production are not deterministic and rather stochastic due to unpredictable future conditions. A distribution function here can help predict the uncertainty since it allows to define the mean value and the standard deviation especially in cases where sufficient data about the past is available [85]. Consequently, this provides an interesting range to work within TCA. Automation of the TCA practices and big datasets provide sufficient data and enable dealing with subjectivity, human intervention, and the variety in scales and units.

TCA requires a dynamic process of measurement and monetisation and is not fixed standardized. This contradicts the current literature that emphasizes that standardisation of sustainability accounting is required [86]. It may be wise to be careful in standardizing all TCA processes or define built-in evaluation mechanisms to prevent metrics from being unable to fully grasp the total impact of products or services.

4.3. Timeliness

Although the standardisation is important to cope with earlier described complexity, it makes the TCA process too static. It must be done with caution not to jeopardize the machine learning effect from big data. In order to make big data applications in TCA function, it is crucial to achieve a degree of timeliness. Complex analysis that requires a lot of computing power may take weeks to arrive at the output. This is extremely costly, and it may not outweigh the benefits of real-time TCA information. This tradeoff should be considered when implementing IT technologies in TCA. Then, TCA and big data may work together to provide more useful information. TCA may look into management accounting literature. The expected value of additional information can be calculated based on different conditions and probabilities [87]. Not all extra details in decision making are essential. It is important to calculate the expected value of relevant decision-making information to determine its maximum price [87]. The cost of establishing the whole data environment that provides the required TCA input should be subtracted here to determine whether combining TCA and big data for timelier information is beneficial. The costs of installing the data environment can be determined accurately and consequently, and the expected value of additional information can be calculated. Bayes' Theorem, based on posterior probabilities and conditional probabilities, is helpful to arrive at the expected value and determine whether additional information is beneficial [88].

4.4. Implementation

During the research, the implementation struggles arrived quickly. The organisation in the energy market seem to await governmental institutions to mandate the establishment of the data environment. Similar to Seele, it seems capturing the concept of sustainability

in an algorithm needs a unified definition and, therefore, involvement of the stakeholders and the legal authorities to make the required data operational [89].

Confidentiality and sharing are important itching issues. Currently, companies most likely already have a lot of data that they keep for themselves. Therefore, establishing an industrial protocol per type of cost is important to enable all parties to collectively provide and exchange their TCA input data in a uniform and transparent manner. Blockchain allows data to be used in the calculation without other parties diving deep into the data to extract sensitive data. It secures ownership of data. The protocol should not come from companies themselves but rather from an independent foundation that checks and owns a protocol; every type of cost should secure the data sharing.

The blockchain is a revolutionary new technology, and its application will be expanded and reconsidered, and all the difficulties over time should be addressed with the help and guidance of a third party to prevent misuse [90]. Given a well-functioning data environment that gathers, processes, and shares TCA input data, analytical tools can perform predictive and descriptive analysis.

It is recommended that the academic and business worlds work together more intensively to deal with the current TCA and IT challenges.

All the implementation barriers should be more extensively studied, and it might be important to link all these barriers to the wider available literature on barriers to sustainability practices i.e., of the circular economy and its barriers as studied by Galvão et al. They adopted bibliometric research and identified barriers in 6 groups: technological, policy and regulatory, financial, and economic, managerial, performance indicators, customers and social [91]. These themes can be used as an umbrella for the implementation barriers identified in TCA. The lack of collaboration and standardisation is related to the policy, regulatory and managerial barriers; the financing hurdle relates to the financial and economic barrier, and the lack of advanced technologies is a technological barrier. This understanding of implementation barriers from broader literature helps study TCA implementation in a broader context.

4.5. Future Research

Besides the recommendation to focus on the literature on the implementation barriers, it is important to dive into establishing protocols for all different types of energy production costs. It is helpful to attempt to collaborate with practitioners to establish a protocol on how to share the relevant TCA input data and in which format. Furthermore, it is important to dive further into the social impact assessment and what role big data could play here. Ethical considerations concerning human rights should be at the bottom of how society, companies, and the environment relate to each other. Much research has already been done on quantifying social values [92,93].

TCA literature should go even further by attaching monetary values to social impacts since that would lead to a better weighting and comparison in all three dimensions and between organisations. At last, it might be helpful in the future to enable the experts within the panel to interact with each other. This would create a different interview dynamic where disciplines come together to search for answers.

4.6. Strengths and Limitations

This research approached a whole new field of research by applying big data, AI, and blockchain technologies into True Cost Accounting combining academic and practitioners' disciplines. Due to its experimental nature, it was important to interview experts from many different relevant research fields. This research was multidisciplinary and internationally oriented since local and top experts participated from the Dutch, Polish, and German energy markets. However, more research is needed. Given the exploratory nature of this study, this study was mainly about providing new insights to TCA literature, i.e., the potential for big data and blockchain applications to cope with complexity, timeliness, and accuracy.

A limitation here might be that when looking at the respondents' insights, one participant showed a contrasting opinion by mentioning that TCA should include ethical consideration before "letting big data loose on it". Other respondents showed enthusiasm about big data's potential for TCA. This might bias the results, and in future research, more critical experts should be engaged.

5. Conclusions

The study categorized the TCA challenges into complexity, accuracy, timeliness, and a fourth group of challenges emerged under "implementation". The study reviewed the current use of big data, AI, and blockchain in accounting literature in answering the research question: What is the current use of big data in management accounting?

The study explored an innovative idea of adopting IT to cope with the TCA challenges. It used an innovative, multidisciplinary, and multinational approach to collect opinions from a diverse group of relevant stakeholders, IT specialists, sustainability and energy experts, and accountants in the European energy market; specifically the Netherlands, Germany, and Poland. It showed ready-to-use technical feasibility of big data infrastructure that measures the TCA impacts, analyses the data, identifies patterns, allocates costs to cost objects, and reduces negative challenges. Simultaneously, it identified barriers concerning financing, and potential standardisation of TCA practices as issues to be solved before the real adoption can start. Although blockchain technology enables creating protocols for all types of energy production costs and assures secure, accurate data sharing between all involved parties, the essential implementation throughout the whole chain, including policy levels, was perceived as most challenging. The study contributes to the literature by categorizing the challenges in TCA application for energy production and presenting. the readiness potential for big data, AI and blockchain to tackle those TCA challenges. Furthermore, it reveals the need for cooperation between accounting and technical disciplines to enable the energy transition. Future research should further explore the implementation barriers, especially the cooperation aspects and establish protocols for blockchain applications to ease the big data TCA application.

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Appendix A

Table A1. Description of the true costs in the cost price of energy generation.

Types of Costs	Description of the Cost
Installation costs	Capital costs encompass all investment cost, refurbishment, assembly, decomposing, and financing costs in an LCOE measure (Samadi, 2017)
Fuel costs	The price of the fuel used for the energy in the LCOE measure
Non-fuel operation and maintenance costs	Non-fuel operations encompass all fixed costs such as wages, insurance, equipment, maintenance costs and variable costs at the power plant via an LCOE measure (Samadi, 2017)
Grid costs	Grid costs can be defined as the extra costs in the transmission and distribution system when power generation from a new plant is integrated into that system (Holttinen et al., 2011).
Balancing costs	The central system operator of the grid, who ensures a stable operation of the energy supply and demand, manages the electrical systems to compensate for unplanned short-term fluctuations in the electricity supply and demand by contracting sufficient reserves ahead of time (Samadi, 2017). This holding of reserves to deal with added flexibility to the grid is being regarded as balancing costs (Mattman et al., 2016).
Profile costs	Profile costs are additional specific capital and operational costs that the energy production from a new plant may cause in the residual electricity system. The extra costs due to the overproduction of renewable energy generation systems are considered to be profile costs (Samadi, 2017)
GHG emission costs	GHG emissions contribute to global warming and thus lead to damages for the society in tackling climate change. The carbon cost for society is used here, reflecting the GHG emission in the energy generation process.
Air pollution	The extraction, transportation and conversion of fossil fuels lead to the release of several forms of pollutants into the environment, such as SO_2, NOx, NMVOC, NH_3, fine particles, Cd, As, Ni, Pb, Hg, Cr, Formaldehyde, Dioxin (Samadi, 2017). They affect the air, water, and soil quality, which affects the health of humans, crops, building materials and the natural environment.
Landscape and noise impacts	The welfare of people is affected by the visual appearance of the power plant, landscape changes or the noise the power plant generates (Samadi, 2017). The valuation of properties may be negatively impacted after changes in the use of the land.
Impacts on biodiversity	Impacts on ecosystems can be in the form of damage to land, plant life or animals. When the damage affects the ability of a plant or an animal species to survive is threatened, biodiversity may be reduced (Epstein et al., 2011).
Employment benefits	Employment will create economic and social benefits for employees, and the government has less cost of unemployment.
Upstream costs	The upstream costs result from the extraction of natural resources (Greenstone & Looney, 2012). Here, upstream activities for operating the power plant have been considered. For the extraction of the resources and production of the required materials for the power plants, much energy is needed, and GHG is emitted (Jensen, 2019). During the transport of the resources and the construction of the power plants, energy use and CO_2 emission are inevitable.
Downstream costs	The costs of the nonrecyclable components of the power plant could be taken into consideration as downstream costs since the nonrecyclable waste streams may affect future generations (Shokrieh & Rafiee, 2020; Jensen, 2019) Source: [16,24,94–98]

Appendix B

Table A2. The list of interviewees participating in the research.

	Name	Respondent Field of Expertise	Duration and Date of the Interview
R1	Florin Schürkens	Master student at University of Groningen who researched the German energy market	04 September 2021: 45 min
R2	Marco Aiello	Expert in application of big data and artificial intelligence, University of Stuttgart	12 April 2021: 45 min
R3	Jeroen Kuper	Expert on the application of IT in accounting and control, in the Netherlands	13 April 2021: 1.5 h
R4	Gideon Laugs	Expert in system integration in the energy market, Energy academy Groningen	14 April 2021: 1 h 45 min
R5	Victor Ipekoglu	Master student at University of Groningen who researched the German energy market	17 April 2021: 45 min
R6	Ruben Bour	TCA expert, Deloitte Netherlands	28 April 2021: 35 min
R7	Harmen-Sytze de Boer	Expert in Modelling of Climate Change at Planbureau voor de Leefomgeving (PBL) in the Netherlands	29 April 2021: 1 h 5 min
R8	Dick de Waard	Prof of Accountancy University of Groningen, Netherlands	11 May 2021: 45 min
R9	Anonymous	Expert on blockchain application in the Dutch energy market	12 May 2021: 30 min
R10	Elly Reinierse	Expert on evaluation of social impacts of mining activities around the globe, The Hague	13 May 2021: 1 h 30 min
R11	Maciej Maciejowski	Expert, implementer in IT and big data, PlanBe Poland	13 May 2021: Respondents 11, 12 and 13 were interviewed together in an expert discussion session duration of 1 h 30 min in total
R12	Agnieszka Maciejowska	Expert, implementer in IT marketing, PlanBe Poland	
R13	Justyna Wojcik	Expert in carbon footprint and sustainability, PlanBe Poland	
R14	Anonymous	Wind turbine owners from northern Poland.	15 June 2021: 5 h
R15	Anonymous	A manager from a company dealing with photovoltaic installation in the southern part of the Masovian Voivodeship.	25 June 2021: 2 h 15 min
R16	Anonymous	The energy industry CEO of a large company dealing in energy production, manager in the energy industry with 25 years of experience.	12 July 2021: 2 h 30 min

Source: own study.

Appendix C

Cost price calculation from Table 2 in the text was central to discuss costs and see how to come to better cost price calculations. Tables 2 and A1 exhibited in the text were sent to the respondents in advance together with the Interview guide. Infographic served as an icebreaker and a brief explanation of the TCA concept to energy and IT experts.

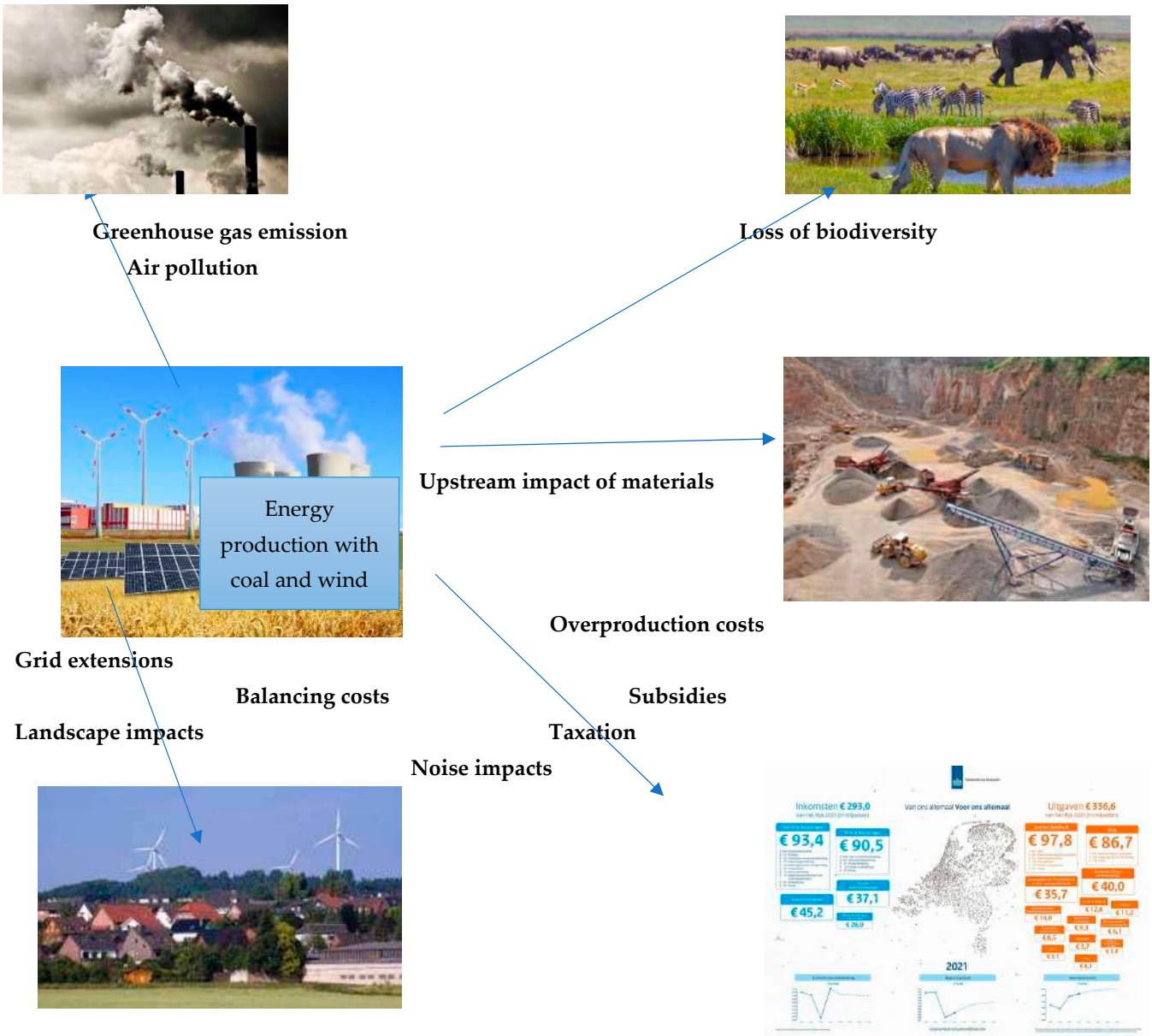

Figure A1. Infographic overview of externalities in energy production.

Thank you for making time for me. I really appreciate it. I want to briefly introduce you to my research topic. Last year I did make a true cost price calculation of energy to see how sustainable energy generation really is. I wanted to include all greenhouse gas emission impacts, air pollution impacts, and landscape impacts to provide a full overview in order to make the comparison between wind and coal energy generation. However, last year I found out that the measurement and valuation of those impacts is challenging and requires expertise from many disciplines than just experts in accounting only, which is my field of discipline. In the energy sectors, many impacts on stakeholders can be identified. An overview of all the impacts is shared with you via the e-mail. The current research aims to explore how big data, AI and maybe blockchain to strengthen the true cost estimations we conducted previously. In the infographic, you see an overview of the impacts of energy generation. The impacts that it has on the air, the nature, the mining areas, the land, the society, and the financing. With that in mind, I wanted to ask you some questions. So let's start.

1. Complexity

To what degree do you think that energy prices do cover external impacts of energy production?

- If not, why do you think that is the case or what is the bottleneck?
- Where do you think the complexity comes from?
- How do you think current energy prices are determined? What influence does the market, regulation and subsidies have?

What do you know about the impacts of energy generation on:

a. Biodiversity
b. GHG emission
c. Air pollution
d. Landscape and noise impacts.
e. Upstream impacts of all materials used in the process of energy generation
f. System impacts
g. Subsidies and taxation

- Consequently, what do you know of the measurement/quantification of those impacts (a–g)
- If the respondent does not know anything on the measurement of the impacts, ask: where would you start in trying to measure the impacts?
- To what degree do you think that is difficult/ do you experience complexity in a sense that there are different metrics and unit?
- What would be the ideal situation to measure those impacts? (e.g., what variables do you need?)
- If you had to value the impacts, where would you start? (e.g., Do you use market values? Do you look at the cost of avoidance? Do you look at the costs needed to restore the damage? Do you look at all the different outputs in the lifecycle assessment and try to attach a value to it?)

What do you know of big data? In what fields?

- TCA requires input from experts of many disciplines, and large numbers of upstream and downstream processes need to be tracked. How can big data help in reducing the complexity?
- When applying big data to measure the impacts of energy production. We need a lot of data points in order be able to determine what processes in energy production lead to what impacts and lead to what costs. Where would you start?
- What information do you need? (e.g., data on actual costs, quantities of elements, conversion of costs, time periods, quality, technical parameters, etc.)
- Where to find that data or what institutions are available in your country that measure most of the information.
- Big data is often unstructured. How to make different units of measurement comparable? What techniques are there available to integrate all dimensions into one single monetary unit?
- Big data can be used to find correlations or forecast costs. How can big data make estimations of the true cost, for example of 1 ton of CO_2 emission, better?
- How would you determine the causality between certain activities and impacts (e.g., How do you assign air pollution due to energy production for example to health? What variables and what correlations do you need?)
- How can big data help in valuing the impact of energy production on climate change, air pollution, biodiversity loss, landscape and noise impacts, subsidies, upstream impacts, system impacts?
- How to make sense of those different units of measurement? How can big data help and what techniques are available to compare or integrate the different units (e.g., use of ratio scales in performance measurement?)

Are you familiar with big data and Artificial intelligence?

- What do you know of AI?
- In what fields and circumstances?
- What role can AI play in reducing the complexity of TCA we just discussed?

2. Accuracy

   To what degree do you think that subjectivity exist in the valuation of that externalities.

   - How do you think that is possible
   - Where does this subjectivity comes from?)
   - In order to assign impacts to energy generation there should be insight in what emission lead to what climate costs and what air pollution lead to what health costs. So there should be an identification of cause and effect relations. How would you identify such cause and effect relations? What processes lead to what impacts and to what costs?
   - When you look for example at biodiversity, biodiversity is vital for us as human and all the things we grow, it shows that it is difficult to assign a value to the biodiversity services. Can big data or AI play a role in reducing the difficulty?
   - What implication can big data have on the cost estimation and its subjectivity? How would the impact of big data on that estimation work?
   - How can big data and AI contribute? (e.g., focus on prediction of costs? Identification of patterns and cause- and effect chains? Classification of costs?)
   - How can big data provide insight in those cause and effect relationships between for example GHG emission costs and climate change, air pollution and health costs/ loss on crops, placement of a power plant and the noise and landscape impacts? Power plant interferences on biodiversity?

   Are you familiar with blockchain? (e.g.,

   - What do you know of Blockchain?
   - How can blockchain be useful to make sure that the data is accurate?)

3. Timeliness

   Do you think it is possible to have real time insight in the impacts of energy production?

   - What about the availability of all the data measurement points as discussed earlier?
   - To what degree is data on biodiversity, GHG emission, air pollution, landscape and noise impacts and subsidies and system impacts available in a real time manner?
   - What needs to happen in order to have real time insight in those impacts? (e.g., does it require a whole paradigm shift in measurement?)
   - To what degree is it the same for all types of impacts of energy production? (e.g., is there a differences between the loss on biodiversity, air pollution costs, GHG emission costs, Landscape and noise impacts and subsidies?)

   How can big data/ AI / Blockchain helps in providing real time measurements?

   - How can those real time measurement be linked to real time valuation techniques to obtain a real time true cost price calculation.
   - Can it be linked to an external database that contains the valuation of a unit of output from the production?)
   - If you see this model of calculating a true cost price with the help of big data and other technological tools evolving, where might we stand in about 10 years?

Those are all the questions I have for you today. I really want to thank you for your time. I think It was really interesting and helpful to get an insight in your ideas about how to measure sustainable performance of energy production. I can definitely move forward with this. Do you have any questions remaining? Or do you want to come back on anything? I will type out the transcript of this interview and I will send it to you so that you are able to determine whether you agree with it.

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