

# UNLOCKING THE POTENTIAL OF DATA-DRIVEN BUSINESS MODELS: AN EMPIRICAL INVESTIGATION INTO THE ROLE OF ECOSYSTEMS AND FAIR DATA USE

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Data-driven business models are expected to stimulate new economic growth by promoting innovation and value creation through data. However, in addition to concerns about privacy and security, there are ongoing discussions about fair data usage at both the EU and global levels. This research analyses how business model change is influenced by the expected economic benefits as well as how involvement in data ecosystems and the adoption of fair data practices can encourage data-driven innovation. We develop and test a structural equation model with a sample of 1,200 European companies. The findings suggest that organizations recognize the potential for new business and innovation opportunities with data-driven business models. Nevertheless, it is essential to engage in data ecosystems and implement fair and sustainable data usage practices in order to realize these benefits.

## Keywords:

fair data practices, data-driven innovation, business model, structural equation model



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## 1 Introduction

Data has become an essential, multi-faceted asset of the modern global economy (Brynjolfsson et al., 2011; Jetzek et al., 2014; Saaristo & Heikkilä, 2022). New business models (BMs) for novel products and services are expected to be developed through creating, sharing, and using data. But regulations are also being put in place to safeguard against the misuse of information and potential threats to privacy and business secrets (e.g., Data Act, 2022; Krämer & Schnurr, 2021). Too strict protection may enforce monopolistic market positions, hinder innovation, increase the costs of heightened surveillance, and limit freedom of expression in the worst case (Gawer & Srnicek, 2021; Zuboff, 2019; Gandhi et al., 2011). These are pertinent issues for individuals, businesses, and governments who are constantly seeking a fair balance between restrictions and freely flowing open data. Despite the differences in viewpoints and associated risks, the data economy is projected to drive future BMs and innovations, offering ample opportunities for all stakeholders, as noted by the European Commission in 2020.

While the literature suggests that firms can leverage digitalization and their big data analytics capabilities to innovate their BMs (Bouwman et al., 2019; Ciampi et al., 2021), the experiences and outcomes of seizing these opportunities vary. Several studies have witnessed challenges in innovating from data due to poor data quality, unclear ownership, or usage rights, among other reasons (Ermakova et al., 2021; Lange et al., 2021; Rantanen et al., 2019; Eriksson & Heikkilä, 2023).

Therefore, it can be concluded that experimenting with data does not automatically translate into innovation. Recent literature, particularly in relation to Industry 4.0, suggests that to overcome these challenges, it is advisable to focus on creating data ecosystems that adopt fair and sustainable data usage practices (Azkan et al., 2022; Hubaux & Juels, 2016). Through such data ecosystems, companies can gain access to additional data sources, increase their opportunities for collaboration, and stay up-to-date on the latest trends and technologies in the industry (Oliveira et al., 2019). Moreover, to ensure that data is processed and used ethically and lawfully, practices of fair and sustainable data usage are becoming increasingly necessary (Bennett, 2019). Few empirical studies have investigated the impact of fair and sustainable data use practices and data ecosystem participation on BMs building on data-driven

innovation. We fill this gap by developing a model to analyse if expected business benefits from the data economy lead to BM changes, and whether participation in data ecosystems and adoption of fair data practices can increase data-driven innovation. The empirical data are collected from 1,200 diverse European companies.

This study contributes to the literature on BMs, especially on data-driven BM, where data is a core ingredient of a company's BM (Trabucchi & Buganza, 2019). Our objective is to deepen the knowledge on how changes in BMs eventually lead to increased data-driven innovation. Data-driven innovation is a representation of how BMs are implemented to enhance the overall performance of the ecosystem and individual companies within it (e.g., Jetzek et al., 2014). The rest of this paper includes a review of the literature, research hypotheses, methodology, findings, discussion, and conclusions.

## 2 Literature review and hypothesis

Several companies have realized the potential advantages of creating new BMs that utilize data as a crucial resource (Hartman et al., 2014). Ciampi et al. (2021) assert that a company's competence in big data analytics positively affects its ability to innovate its BM. Bouwman et al. (2019) revealed that companies that actively utilize social media, big data, and information technology can increase their performance by transforming their BMs and strengthening their capacity for innovation.

A BM describes how a company creates, delivers, and captures value (Teece, 2010). Companies respond to continuously evolving environments by modifying their BMs (Marolt et al., 2018; Pucihar et al., 2019). These **BM changes** can range from modest refinements to some BM elements to a complete overhaul of the entire BM (Saebi et al., 2017; Eriksson et al., 2022). Companies often make these changes to achieve strategic goals such as increasing profitability, expanding their business, or entering new markets (Heikkilä et al., 2018). Thus, On the basis of research literature, we could assume if a company sees **potential benefits from data**, it is motivated to change its BM (Bucherer et al., 2012; Hartmann et al., 2013; Lindgardt et al., 2009; Pohle and Chapman, 2006; Lafiti et al., 2021a,b). However, to date, there is no clear

empirical evidences showing this relationship. Thus, we propose the following hypothesis (see also Fig.1):

*H1. Potential benefits from data has a significant positive effect on BM change*

Generating economic value via data-driven innovation is seldom achievable by a lone organization. Rather, this process is said to necessitate involvement in **data ecosystems** (Hein et al., 2019), which refer to networks of entities that interact to exchange, create, and utilize data (Oliveira and Lóscio, 2018). To unlock the potential of data-driven business, companies need to share data and collaborate with other parties such as companies, government agencies, users, and other stakeholders. By doing so, they gain access to a broader range of data, which can be used to create new products and services for markets. Furthermore, collaborating with other companies enables them to leverage complementary skills and expertise, accelerating innovation. Therefore, it is not surprising that a recent survey found that approximately one third of organizations are collaborating with partners to exchange data (MIT, 2021). There are several types of data ecosystems, which differ on their control, openness, participant interdependence and purpose (Gelhaar et al., 2021; Curry & Ojo, 2020). For instance, the data ecosystem may be centered around a keystone actor, or it can be a platform or marketplace (Gelhaar et al., 2021). They may also be collaboratively developed and influenced by various actors (De Reuver et al., 2018), such as European data ecosystem is International Data Spaces (Otto & Jarke, 2019), but a data ecosystem could also be formed between just a few companies. We expect that changes in BM would increase a company's activity in data ecosystems:

*H2. BM change has a significant positive effect on participation to data ecosystems*

Companies face various challenges when leveraging data-driven opportunities, such as ensuring secure data sharing, complying with privacy regulations, and controlling personal and private data (MIT, 2021). Additionally, companies must respect copyright, intellectual property, and non-disclosure requirements. To address concerns about potential data misuse, companies can combine their new BMs with practices that promote fair and sustainable data usage. These practices ensure that the company creates services and data-based products in an ethical, fair manner. In

a data economy, fairness requires protecting individuals' rights, respecting businesses' rights and contracts, and taking into account the needs of all stakeholders (Parikka et al., 2021). Practices that promote fair and sustainable data usage create trust, which is often a prerequisite for accessing customer data and building long-term relationships. Researchers note that simply complying with legal requirements is insufficient, and explicit approaches and processes must be adopted to promote fair data usage (Vermanen et al., 2022). Furthermore, we anticipate that participating in data ecosystems could enhance the adoption of fair and sustainable data usage practices (Koskinen et al., 2019)."

*H3. BM changes are positively related to fair & sustainable data usage practices.*

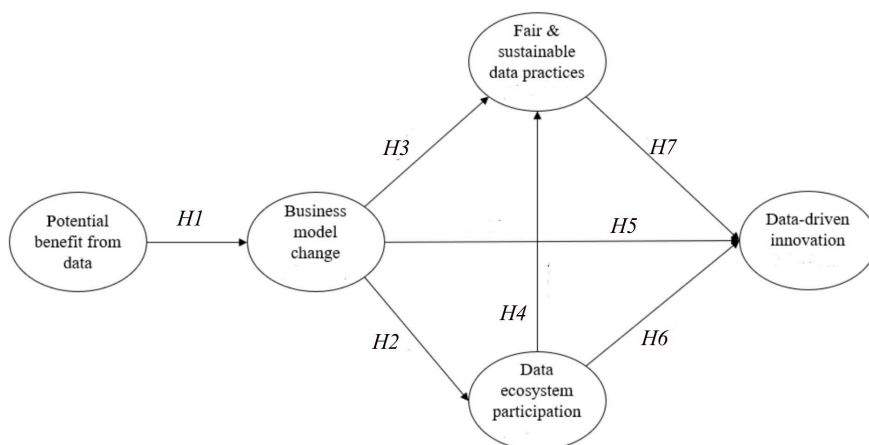
*H4. Participation in data ecosystems has a significant positive effect on fair & sustainable data usage practices.*

Data-driven innovation refers to innovation that utilizes data as a core ingredient. The literature describes it as business innovation that is based on exploiting data and is capable of generating positive economic and social impacts (Jetzek et al., 2014). Companies utilize data to inform decision-making, improve organizational processes, or create customer value (Brynjolfsson et al., 2011). Empirical studies evidence how, for example, by collecting and analyzing data from users (Trabuchi & Buganza, 2019) or other sources (Jetzek et al., 2014), a company can gain insights into how its customers value its products and services and how the company could add even more value to the market. We aim to analyze whether changes to the BMI increase data-driven innovation directly or whether participation in data ecosystems or practicing fair and sustainable use of data leads to increased data-driven innovation:

*H5. BM changes have a significant positive effect on data-driven innovation*

*H6. Participation in data ecosystems has a significant positive effect on data-driven innovation*

*H7. Fair & sustainable data usage practices have a significant positive effect on data-driven innovation*



**Figure 1: Research model**

### 3 Methodology

#### 3.1 The measures

Researchers have developed various measurement scales for assessing changes or innovations in BMs. Some scales focus on the scope of BM change, which evaluates architectural and modular changes in the BM (Spieth & Schneider, 2016; Foss & Saebi, 2017; Lafiti et al., 2021a, b; Eurostat, 2022; Bashir et al., 2023). Novelty scales, in turn, measure the degree of change in an enterprise or industry (Claus, 2017; Marolt et al., 2018; Pucihar et al., 2019). Also, there are scales that measure disruptiveness of changes (Karimi & Walter, 2016), the novelty of digital innovation (Soluk et al., 2021), or the sustainability of changes (Bashir et al., 2022).

Many researchers link changes in a BM to changes in its components. The widely adopted BM Canvas (Osterwalder et al., 2005; Osterwalder & Pigneur, 2010) depicts customer relationships and segmentation, channels, value proposition, key activities, key resources, partners, and the revenue model as components of BM. Both researchers and practitioners use the BM Canvas to analyse BMs and changes in BMs (Lafiti et al., 2021b). Even Eurostat (2022) introduced a scale for BM change in the community innovation survey (CIS) for the first time in 2022. Therefore, this study measures BM changes (i.e., the scope of BM innovation) using a subset of

seven BM components that follow the structure of the BM Canvas (Osterwalder & Pigneur, 2010).

In this study, potential benefits from data-driven innovations were measured by three items (Heikkilä et al., 2018): First, the respondents were to consider how much potential they see in data economy to *increase revenue from the current BM*; secondly, whether they can find *new revenue streams from innovations*; or, thirdly, *to save costs*. Participation in data ecosystems was inquired with questions if the company is *a partner* or *a facilitator* of data ecosystem(s). Fair and sustainable data usage practices consists of a set of eight questions measuring e.g. *ethical code of conduct*, *transparency*, *privacy*, *data sovereignty* (Parikka et al., 2021; Vermanen et al., 2022). Data-driven innovation was measured with two questions on *continuous improvement and innovation of products and services* (e.g. Boer & Gertsen, 2003), and with questions on the use of data to *enhance customer experience*, and *creating value for society, people, and environment* (Sitra, 2021). The constructs and questions are provided in Appendix.

### 3.2 Survey administration, sample and data collection

The survey was conducted in four countries - Finland, France, Germany, and the Netherlands - in 2021, and was commissioned by the Finnish Innovation Fund Sitra<sup>1</sup>. The research data was collected from a B2B decision-maker panel, consisting of professionals holding key decision-making roles, such as CxOs of data, digitalization, information systems, strategy, marketing, and business development. Table 1 provides background characteristics of the sample, with equal strata for the countries, and with close to equal number of respondents from large, medium, small, and micro-sized companies (excluding sole proprietors) in each country. No quotas were defined on industry or activity in the data economy. The raw data set is openly available from Sitra (2021).

Our interest in the potential of data economy to change BMs seems reasonable: More than 80% of the sampled companies foresaw the potential of data economy in creating a competitive edge (Saaristo & Heikkilä, 2022; Ulander et al. 2021).

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<sup>1</sup> Sitra is a fund, which has a special national level role in Finland, because it is accountable and reports directly to the Finnish Parliament. Its capital was granted by the Finnish Parliament.

**Table 1: Profile of respondents' companies**

Variable	Category	%
Country	Finland	25
	France	25
	Germany	25
	The Netherlands	25
Firm size (turnover €)	Micro (under 2 million)	28.1
	Small (2 – 10 million)	26.6
	Medium (10 – 50 million)	22.1
	Large (over 50 million)	23.2
Industry sector	Service activities	15.97
	Manufacturing	11.34
	Information and communication	9.83
	Human health and social work	8.07
	Financial and insurance activities	7.98
	Wholesale and retail trade	6.64
	Other	40.17

The survey data contained some missing values, which were less than 5 % of the total values in the dataset. Therefore, the mean imputation method was used to deal with missing values (Hair et al., 2021).

Cross sectional surveys measuring both dependent and independent variables simultaneously are prone to common method variance (Kock et al., 2021), so in our study we use Harman's single factor test to assess it. The principal axis factoring based first factor accounted for the 35.73 percent of the overall variance. The small size (i.e. below 70%, Kock et al., 2021) of single factor accounted variance confirms the absence of a common method variance problem in our dataset.

#### 4 Data analysis and findings

Partial least squares structural equation modeling (PLS-SEM) was used to test the hypotheses. The guidelines provided by Hair et al. (2021) were followed to test the hypotheses. We used SmartPLS 4.0 software for data analysis.

#### **4.1 Reliability and validity**

We tested first model's reliability (indicator reliability, Cronbach's alpha and composite reliability) and then convergent validity in Table 2 and discriminant validity in Table 3.

The factor loading for an item is recommended to be at least 0.60 (Hair et al., 2021). As shown in Table 1, all items have a higher value than the recommended threshold. Moreover, both the values of Cronbach's alpha and composite reliability are above the recommended threshold value of minimum 0.70. Thus, internal consistency and reliability are confirmed. Convergent validity was examined by computing average variance extracted (AVE). The value of at least 0.50 is suggested as a threshold (Hair et al., 2021). As Table 2 shows, all constructs passed the threshold.

For discriminant validity, the Fornell and Larcker criterion was used, which requires the square root of the AVE of each construct to be higher than its correlation with other constructs (Wong, 2013). Table 3 shows the fulfilment of this criterion and thus the establishment of discriminant validity.

Last, HTMT is used to compare the correlations between indicators measuring different constructs (heterotrait correlations) to the correlations between indicators measuring the same construct (monotrait correlations). If the heterotrait correlations are significantly higher than the monotrait correlations, it suggests that the measures are not distinct and that there may be issues with discriminant validity. HTMT values closer to 0 indicate better discriminant validity and 0.85 is often used as a conservative cut-off point, while a value of 0.90 is considered more liberal (Henseler et al., 2015). The HTMT values in Table 4 were all lower than 0.73, indicating that there were no issues with discriminant validity.

**Table 2: Measurement statistics of first-order constructs**

Construct	Indicator loadings	Cronbach's alpha	Composite reliability	Average variance extracted (AVE)
<i>Potential Benefit from data</i>		0.86	0.92	0.79
Item 1	0.90			
Item 2	0.91			
Item 3	0.85			
<i>BM change</i>		0.89	0.91	0.60
Item 1	0.74			
Item 2	0.75			
Item 3	0.80			
Item 4	0.79			
Item 5	0.76			
Item 6	0.78			
Item 7	0.81			
<i>Data ecosystem participation</i>		0.90	0.94	0.83
Item 1	0.90			
Item 2	0.91			
Item 3	0.92			
<i>Fair &amp; sustainable data usage practices</i>		0.90	0.92	0.58
Item 1	0.78			
Item 2	0.82			
Item 3	0.74			
Item 4	0.75			
Item 5	0.72			
Item 6	0.73			
Item 7	0.78			
Item 8	0.73			
<i>Data-driven innovation</i>		0.74	0.83	0.55
Item 1	0.71			
Item 2	0.76			
Item 3	0.71			
Item 4	0.77			

**Table 3: Discriminant validity of the constructs - Fornell-Larcker Criterion**

	(a)	(b)	(c)	(d)	(e)
<i>Potential benefit from data (a)</i>	<b>0.887</b>				
<i>BM change (b)</i>	0.387	<b>0.775</b>			
<i>Data ecosystem participation (c)</i>	0.611	0.428	<b>0.910</b>		
<i>Fair &amp; sustainable data usage practices (d)</i>	0.614	0.326	0.583	<b>0.758</b>	
<i>Data-driven innovation (e)</i>	0.594	0.349	0.515	0.651	<b>0.739</b>

Bold numbers represent the square roots of the AVEs

**Table 4: Heterotrait–monotrait ratio of correlations (HTMT)**

	(a)	(b)	(c)	(d)
<i>Potential benefit from data (a)</i>				
<i>BM change (b)</i>	0.440			
<i>Data ecosystem participation (c)</i>	0.694	0.479		
<i>Fair &amp; sustainable data usage practices (d)</i>	0.681	0.352	0.626	
<i>Data-driven innovation (e)</i>	0.693	0.394	0.557	0.729

## 4.2 Structural model findings

Next, relationships between constructs were analysed using path coefficients and significance levels. We examined the effect size using Cohen's  $f^2$ , which reflects the effect of an exogenous variable on an endogenous variable (Cohen, 1988).  $f^2$  values greater than 0.02, 0.15, and 0.35 indicate small, moderate, and large effect sizes, respectively. However, as noted in previous studies, finding large effect sizes is rather uncommon in management research (Mazen et al., 1987, p. 406; Strauch, 2019).

Results presented in Figure 2 confirm that all the hypotheses tested in this study are statistically significant. Firstly, we found that potential benefits from data have a clear positive correlation with BM change (H1:  $\beta = 0.39$ ,  $f^2 = 0.18$ ,  $p < 0.001$ ). Secondly, BM change was found to significantly increase participation in data ecosystems (H2:  $\beta = 0.43$ ,  $f^2 = 0.23$ ,  $p < 0.001$ ), which, in turn, is strongly and positively correlated with fair and sustainable data usage practices (H4:  $\beta = 0.54$ ,  $f^2 = 0.37$ ,  $p < 0.001$ ). Thirdly, business model change is found to enhance data-driven innovation, although the effect is small (H5:  $\beta = 0.11$ ,  $f^2 = 0.02$ ,  $p < 0.001$ ). Finally, we observed that while data ecosystem participation has a small effect, fair and sustainable data

usage practices have a large positive impact on data-driven innovation (H6:  $\beta=0.17$ ,  $f^2 = 0.03$ ,  $p < 0.001$ ; H7:  $\beta=0.52$ ,  $f^2 = 0.33$ ,  $p < 0.001$ ).

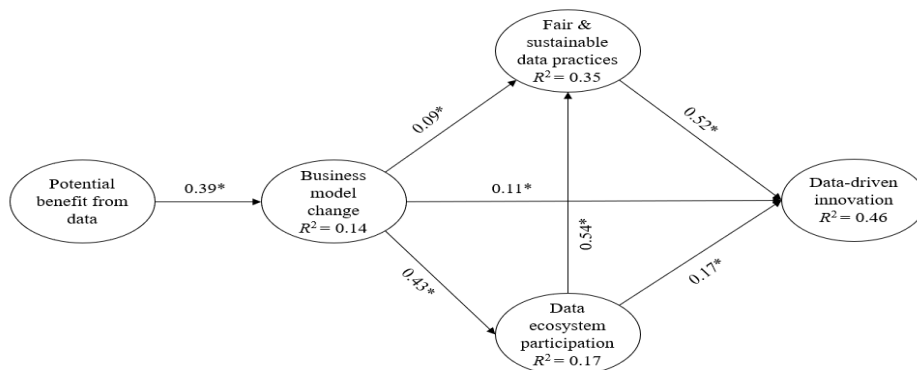


Figure 2: PLS-SEM analysis results. Notes: \* $p < 0.001$  (two-sided test)

## 5 Discussion

### 5.1 Theoretical contributions

This article is among the first to present a comprehensive perspective on data-driven innovation in business, arguing that for companies to benefit from the data, they must first modify their BMs. Empirical evidence presented in our study corroborates prior research (MIT, 2021; Azkan et al., 2022; Hubaux & Juels, 2016; Bennett, 2019), emphasizing the critical role of BM change in driving data-driven innovation.

Moreover, our study found that the more European companies anticipate financial benefits from usage of data, the more likely they are to change their BMs. Specifically, companies expect to gain by introducing new revenue streams from innovative products or services, enhancing their revenue from existing business, or reducing costs. Thus, our empirical results confirm previous literature (Heikkilä et al., 2018) that companies' expected benefits positively relate to BM change, here in the context of the data economy.

However, making changes to BMs alone is not enough. This study underscores the importance of fair and sustainable data usage practices, as well as active engagement in data ecosystems, as key enablers of data-driven innovation in European companies. This highlights the urgent need for more research and development of IS methods, tools, and data usage that are based on principles of fair and sustainable data practices, as previously proposed in studies such as Nahr & Heikkilä (2022), Alt & Klein (2011), and Pucihar (2020). This need is becoming increasingly urgent in the context of artificial intelligence and machine learning, as noted by Seppälä et al. (2021).

## **5.2 Managerial implications**

The findings suggest that the companies which aim at seizing the benefits from data economy by data-driven innovations should, 1) change their BM, 2) be prepared to take part in data ecosystems and 3) take measures to ensure the fair and sustainable data use. Appropriate BM, a suitable network of partners, and ethically sound practices for handling data make it possible to engage and increase innovation from data. BM tools - such as <https://businessmakeover.eu/> and data-driven services card game (Breitfuss et al., 2023) - are available to define the changes in BM.

Regarding data ecosystems, there are several local, regional, national and European industry specific innovation ecosystems and data spaces that welcome companies to join and co-create data driven new services. These ecosystems provide opportunities not only to share experiences from the data economy but also to share open data among partners or provide reference architectures and interfaces to data assets, as suggested by the Digital Single Market regulatory package within the limits of privacy and intellectual property protection. In the future, sandboxed development of data-driven BMs and services will be required for conformity assessment and accreditation of the ethical and rightful treatment of data. Therefore, data ecosystems are increasingly necessary in promoting practices for fair and sustainable data usage.

## 6 Conclusions

This study provides evidence that the perceived economic potential from data economy serves as a motivation for a company to change its BM, which, in turn, leads to data-driven innovation through increased participation in data ecosystems and the implementation of fair and sustainable data practices. Overall, our study suggests that the data economy can provide a competitive advantage to companies, but it must be implemented in an ethical and responsible manner. These findings have important implications for businesses seeking to leverage data-driven innovation to achieve business benefits. Specifically, companies must engage in data ecosystems and adopt responsible data usage practices to comply with data protection regulations and maintain ethical use of data.

This study has some limitations that need to be taken into consideration when interpreting the results. Firstly, the data was collected from four European countries only, and therefore, the results may not be generalizable to companies in other regions, such as the United States and China, which have different regulatory environments and attitudes towards fair and sustainable data practices. Further research is required to explore how multinational companies can effectively promote ethical data usage across diverse regulatory environments. Also, it is crucial to examine the validity of ethical data practices and European data sharing ecosystems outside the scope of European legislation. Secondly, the cross-sectional nature of the survey could introduce response bias, as firms at different stages of their innovation trajectories may hold varying views on data-driven innovation. However, the inclusion of a large sample size is expected to mitigate such variance. It is important to note that this study analysed companies of all sizes. Nevertheless, it is worth mentioning that small and medium-sized enterprises (SMEs) often lag behind in digitalization and digital transformation efforts, resulting in missed opportunities for innovation. Therefore, we recommend that future research places particular emphasis on exploring data-driven innovation and business models within SMEs. Thirdly, future research could examine in more detail how participation in data ecosystems enables the development of data-driven services by companies. Although ecosystems play a significant role in generating collective intelligence and supporting the introduction of new business innovations, the priorities of such ecosystems vary (Elia et al., 2020). Therefore, it would be interesting to do qualitative

studies on the reasons behind a company's participation in an ecosystem and how they can leverage collective intelligence to their benefit. Last, large data-driven organisations may utilize data governance for allocating authority and control over data and making data-related decisions (Janssen et al., 2020). This points to need for further research of data governance in the context of data-driven business, and its impact on strategies for data ecosystems and ethical data practices.

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## Appendix

## Constructs and items

<i>Construct</i>	<i>Item</i>
<b><i>Potential Benefit from data</i></b>	<b>How much potential you see in the data economy to... (Scale: 1 = Strongly disagree...5 = Strongly agree)</b>
<i>Item 1</i>	Create additional revenue from current business model?
<i>Item 2</i>	Create new revenue streams from innovations
<i>Item 3</i>	Saving costs
<b><i>BM change</i></b>	<b>Has your company made significant changes in the business model (for example the following elements) during the last two years? (Scale: 1= No, none, 2= Yes, some, 3= Yes, significant)</b>
<i>Item 1</i>	Customers (Example: Traditionally we have been B2B company only but now we also/only have consumer customers.)
<i>Item 2</i>	Channels (Example: Traditionally we have sold our products through wholesalers but we have now opened up e-commerce site for direct access.)
<i>Item 3</i>	Value proposition (Example: Previously we have sold products but now we offer services where our own and others' products are part of.)
<i>Item 4</i>	Activities (Example: We have stopped or started new activities - previously we have been purely a hardware company but now we have software coding also.)
<i>Item 5</i>	Resources (Example: We have acquired new or discarded old resources (factories, people, skills).)
<i>Item 6</i>	Partners (Example: We have new partners helping us in creation and production of our value proposition to our customers, e.g. offshoring, near-shoring.)
<i>Item 7</i>	Revenue models (Example: From one-off transactions to time-based subscription.)
<b><i>Data ecosystem participation</i></b>	<b>How well do the following statements describe the current status of your company? (Scale: 1 = does not describe at all ... 5 = describes very well)</b>
<i>Item 1</i>	Our company is part of one or more data ecosystems

<i>Construct</i>	<i>Item</i>
<i>Item 2</i>	We are planning to facilitate data ecosystems
<i>Item 3</i>	Our company is the facilitator of one or more data ecosystems
<b><i>Fair &amp; sustainable data usage practices</i></b>	<b>Please indicate whether the following objectives of data use are taken into practice in your company (Scale: 1 = totally disagree ... 5 = totally agree)</b>
<i>Item 1</i>	We offer our customers easy tools to access and manage their personal and/or business data
<i>Item 2</i>	We communicate about the use of data in our corporate social responsibility reporting
<i>Item 3</i>	Data we gather from consumers is available for them to use in other services outside our company
<i>Item 4</i>	We have defined ethical rules for our organization for using, collecting and sharing data
<i>Item 5</i>	We strive to create trust by acting and behaving transparently
<i>Item 6</i>	Our digital services are designed to respect privacy
<i>Item 7</i>	Our digital services are designed to respect control over personal and business data
<i>Item 8</i>	Company's consideration of the rights of individuals and/or organizations exceeds statutory requirements
<b><i>Data-driven innovation</i></b>	<b>From the following data economy related statements, choose how well they describe your company's current business. (Scale 1 = does not describe at all ... 5 = describes very well)</b>
<i>Item 1</i>	In product development, we primarily invest in continuous and gradual improvements in our products.
<i>Item 2</i>	We wish to complement our data from several different data sources and interactive situations so that we can create the best possible experience for our customers.
<i>Item 3</i>	We continuously invest in the innovation of new products / services
<i>Item 4</i>	We create value from data, not just for our operations, but also for society, people, and environment.

