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

MARIKKA HEIKKILÄ, FARHAN AHMAD, JUKKA HEIKKILÄ
University of Turku, Turku School of Economics, Finland
marikka.heikkila@utu.fi, farhan.ahmad@utu.fi, jups@utu.fi

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

University of Maribor Press

DOI https://doi.org/10.18690/um.fov.6.2023.6
ISBN 978-961-286-804-8

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 (Trabucci & 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 change**s 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

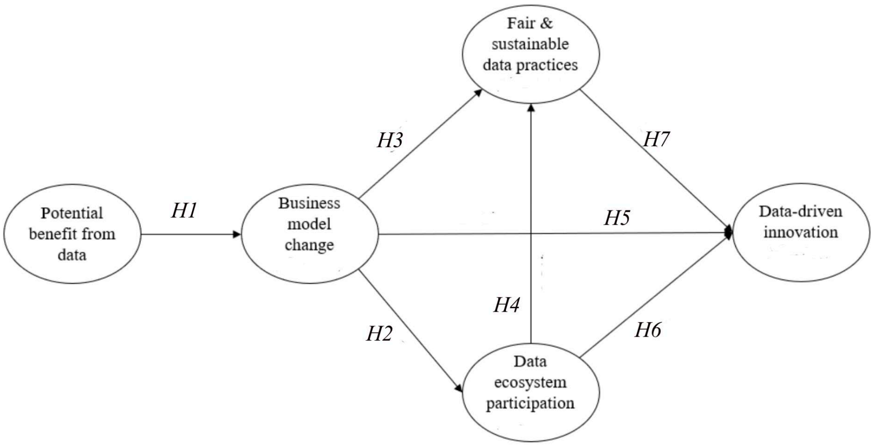

Figure 1: Research model

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 (Clauss, 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[1]. 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).

[1] 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)
Potential Benefit from data		0.86	0.92	0.79
Item 1	0.90			
Item 2	0.91			
Item 3	0.85			
BM change		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			
Data ecosystem participation		0.90	0.94	0.83
Item 1	0.90			
Item 2	0.91			
Item 3	0.92			
Fair & sustainable data usage practices		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			
Data-driven innovation		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)*
Potential benefit from data (a)	**0.887**				
BM change (b)	0.387	**0.775**			
Data ecosystem participation (c)	0.611	0.428	**0.910**		
Fair & sustainable data usage practices (d)	0.614	0.326	0.583	**0.758**	
Data-driven innovation (e)	0.594	0.349	0.515	0.651	**0.739**

Bold numbers represent the square roots of the AVEs

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

	(a)	*(b)*	*(c)*	*(d)*
Potential benefit from data (a)				
BM change (b)	0.440			
Data ecosystem participation (c)	0.694	0.479		
Fair & sustainable data usage practices (d)	0.681	0.352	0.626	
Data-driven innovation (e)	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: β=0.17, f^2 = 0.03, $p < 0.001$; H7: β=0.52, f^2 = 0.33, $p < 0.001$).

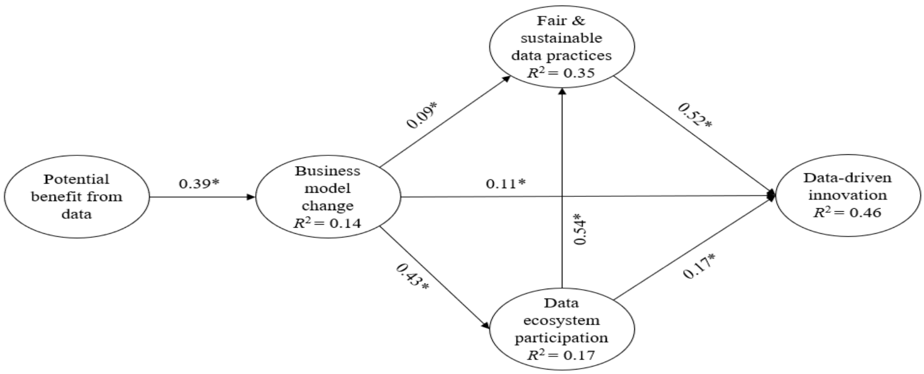

Figure 2: PLS-SEM analysis results. Notes: *p < 0.001 (two-sided test)

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 at 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.

Acknowledgements

We express our gratitude to Sitra for sharing their data, which was invaluable to our research. Their commitment to open data has greatly contributed to advancing knowledge in this area and has allowed us to draw meaningful insights from the data.

References

Alt, R., & Klein, S. (2011). Twenty years of electronic markets research – Looking backwards towards the future. *Electronic Markets*, 21(1), 41–51. https://doi.org/10.1007/s12525-011-0057-z

Azkan, C., Möller, F., Ebel, M., Iqbal, T., Otto, B., & Poeppelbuss, J. (2022). Hunting the Treasure: Modeling Data Ecosystem Value Co-Creation, Forty-Third International Conference on Information Systems, Copenhagen 2022.

Bashir, M., Alfalih, A., & Pradhan, S. (2023). Managerial ties, business model innovation & SME performance: Moderating role of environmental turbulence. *Journal of Innovation & Knowledge*, 8(1), 100329.

Bashir, M., Alfalih, A., & Pradhan, S. (2022). Sustainable business model innovation: Scale development, validation and proof of performance. *Journal of Innovation & Knowledge*, 7(4), 100243.

Bennett, S. (2019). Governance in practice: Big data, privacy and information governance-incorporating an ethical-based assessment. *Governance Directions*, 71(5), 244-254.

Boer, H., & Gertsen, F. (2003). From continuous improvement to continuous innovation: a (retro)(per)spective. *International Journal of Technology Management*, 26(8), 805-827.

Bouwman, H., Nikou, S., & de Reuver, M. (2019). Digitalization, business models, and SMEs: How do business model innovation practices improve performance of digitalizing SMEs?. *Telecommunications Policy*, *43*(9), 101828.

Breitfuss, G., Santa-Maria, T., Fruhwirth, M., & Disch, L. (2023). Use Your Data: Design and Evaluation of a Card-Based Ideation Tool for Data-Driven Services. HICSS 2023, Retrieved from: https://scholarspace.manoa.hawaii.edu/items/b3df1410-42f5-4136-ac28-95f934a1a67c

Brynjolfsson, E., Hitt, L. M., & Kim, H. H. (2011). Strength in numbers: How does data-driven decision making affect firm performance? *SSRN Electronic Journal*, doi:10.2139/ssrn.1819486

Bucherer, E., Eisert, U. & Gassmann, O. (2012). Towards systematic business model innovation: Lessons from product innovation management. *Creativity and Innovation Management*, 21(2), pp. 183–198.

Ciampi, F., Demi, S., Magrini, A., Marzi, G., & Papa, A. (2021). Exploring the impact of big data analytics capabilities on business model innovation: The mediating role of entrepreneurial orientation. *Journal of Business Research*, 123, 1-13.

Clauss, T. (2017). Measuring business model innovation: Conceptualization, scale development, and proof of performance. *R&D Management*, 47(3), 385-403.

Cohen J. E. (1988). Statistical Power Analysis for the Behavioral Sciences. Hillsdale, NJ: Lawrence Erlbaum Associates, Inc.

Curry, E. & Ojo, A. (2020). Enabling Knowledge Flows in an Intelligent Systems Data Ecosystem, in Real-time Linked Dataspaces: Enabling Data Ecosystems for Intelligent Systems, E. Curry (Ed). Springer: Cham, Switzerland.

Data Act (2022). Data Act: Proposal for a Regulation on harmonised rules on fair access to and use of data. Retrieved from: https://digital-strategy.ec.europa.eu/en/library/data-act-proposal-regulation-harmonised-rules-fair-access-and-use-data

De Reuver, M., Sørensen, C., & Basole, R. C. (2018). The digital platform: a research agenda. *Journal of Information Technology*, 33(2), 124–135. https://doi.org/10.1057/s41265-016-0033-3

Elia, G., Margherita, A., & Passiante, G. (2020). Digital entrepreneurship ecosystem: How digital technologies and collective intelligence are reshaping the entrepreneurial process. *Technological Forecasting and Social Change*, 150, 119791.

Eriksson, T. & Heikkilä, M. (2023). Capabilities for data-driven innovation in B2B industrial companies, *Industrial Marketing Management*, 111, 158-172. https://doi.org/10.1016/j.indmarman.2023.04.005

Eriksson, T., Heikkilä, M. & Nummela, N. (2022). Crafting SME Business Model for International Expansion with Data-Driven Services, in Business Models and Firm Internationalisation, Christian Nielsen, Svetla T. Marinova, Marin A. Marinov (eds.) in the series of Routledge Frontiers in the Development of International Business, Management and Marketing

Ermakova, T., Blume, J., Fabian, B., Fomenko, E., Berlin, M., & Hauswirth, M. (2021). Beyond the hype: why do data-driven projects fail?. Proceedings of the 54th Hawaii International Conference on System Sciences.

European Commission. (2020). *The European Data Strategy*. Brussels: European Commission. Retrieved from https://ec.europa.eu/commission/presscorner/detail/en/fs_20_283

Eurostat (2022). Community Innovation Survey (CIS): Questionnaire library, QUESTION - Business model changes, Retrieved from https://ec.europa.eu/eurostat/cache/website/cis/Questions/Question_BUSSMOD.html

Foss, N. J., & Saebi, T. (2017). Fifteen years of research on business model innovation: How far have we come, and where should we go?. *Journal of management*, 43(1), 200-227.

Gandhi, R., Sharma, A., Mahoney, W., Sousan, W., Zhu, Q., & Laplante, P. (2011). Dimensions of cyber-attacks: Cultural, social, economic, and political. *IEEE Technology and Society Magazine*, 30(1), 28-38.

Gawer, A. & Srnicek, N. (2021). Online platforms: economic and societal effects, EPRS European Parliamentary Research Service: Brussels, Belgium Retrieved from: https://www.europarl.europa.eu/RegData/etudes/STUD/2021/656336/EPRS_STU(2021)656336_EN.pdf

Gelhaar, J., Groß, T., & Otto, B. (2021). A taxonomy for data ecosystems. Proceedings of the 54th Hawaii International Conference on System Sciences

Hair Jr, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2021). *A primer on partial least squares structural equation modeling (PLS-SEM)*. Sage publications.

Hartmann, M., Oriani, R. & Bateman, H., (2013). The performance effect of business model innovation: An empirical analysis of pension funds. Proceedings of the 35th DRUID Celebration Conference, pp. 17-19.

Hartmann, P. M., Zaki, M., Feldmann, N., & Neely, A. (2014). Big data for big business? A taxonomy of data-driven business models used by start-up firms. *Cambridge service alliance*, 1-29.

Heikkilä, M., Bouwman, H., & Heikkilä, J., (2018). From strategic goals to business model innovation paths: an exploratory study. *Journal of Small Business and Enterprise Development*, 25 (1), 107–128. https://doi.org/10.1108/JSBED-03-2017-0097.

Hein, A., Weking, J., Schreieck, M., Wiesche, M., Böhm, M., & Krcmar, H. (2019). Value co-creation practices in business-to-business platform ecosystems. *Electronic Markets*, *29*, 503-518.

Henseler, J., Ringle, C.M., Sarstedt, M., 2015. A new criterion for assessing discriminant validity in variance-based structural equation modelling. *Journal of the Academy of Marketing Science*, 43, 115–135. https://doi.org/10.1007/s11747-014-0403-8

Hubaux, J. P., & Juels, A. (2016). Privacy is dead, long live privacy. *Communications of the ACM*, 59(6), 39-41.

Janssen, M., Brous, P., Estevez, E., Barbosa, L. S., & Janowski, T. (2020). Data governance: Organizing data for trustworthy Artificial Intelligence. *Government Information Quarterly*, *37*(3), 101493.

Jetzek, T., Avital, M., & Bjorn-Andersen, N. (2014). Data-driven innovation through open government data. *Journal of Theoretical and Applied Electronic Commerce Research*, 9(2), 15-16. doi:10.4067/S0718-18762014000200008

Karimi, J., & Walter, Z. (2016). Corporate entrepreneurship, disruptive business model innovation adoption, and its performance: The case of the newspaper industry. *Long range planning*, 49(3), 342-360.

Kock, F., Berbekova, A., & Assaf, A. G. (2021). Understanding and managing the threat of common method bias: Detection, prevention and control. *Tourism Management*, 86, 104330.

Koskinen, J., Knaapi-Junnila, S. & Rantanen, M.M. (2019). What if we Had Fair, People-Centred Data Economy Ecosystems?, 2019 IEEE SmartWorld, Ubiquitous Intelligence & Computing, Advanced & Trusted Computing, Scalable Computing & Communications, Cloud & Big Data Computing, Internet of People and Smart City Innovation (SmartWorld/SCALCOM/UIC/ATC/CBDCom/IOP/SCI), Leicester, UK, 2019, pp. 329-334, doi: 10.1109/SmartWorld-UIC-ATC-SCALCOM-IOP-SCI.2019.00100.

Krämer, J. & Schnurr, D. (2021). Big data and digital markets contestability: Theory of harm and data access remedies, *Journal of Competition Law & Economics*, 18(2) 255–322, https://doi.org/10.1093/joclec/nhab015

Latifi, M. A., Bouwman, H., & Nikou, S. (2021a). ICT-Driven Business Model Innovation in SMEs: The Role of Organizational Capabilities, Firm Size and Age. BLED 2021 Proceedings

Latifi, M. A., Nikou, S., & Bouwman, H. (2021b). Business model innovation and firm performance: Exploring causal mechanisms in SMEs. *Technovation*, *107*, 102274.

Lange, H. E., Drews, P., & Höft, M. (2021). Realization of Data-Driven Business Models in Incumbent Companies: An Exploratory Study Based on the Resource-Based View. *ICIS 2021 Proceedings*.

Lindgardt, Z., Reeves, M., Stalk, G & Deimler, M. S. (2009). Business Model Innovation, When the Game Gets Tough, Change the Game, Boston: The Boston Consulting Group.

Marolt, M., Lenart, G., Borstnar, M. K., Vidmar, D., & Pucihar, A. (2018). SMEs Perspective on Business Model Innovation. 31th Bled eConference Digital Transformation – Meeting the Challenges (June 17 - 20, 2018, Bled, Slovenia).

Mazen, A. M. M., Hemmasi, M., & Lewis, M. F. (1987). Assessment of statistical power in contemporary strategy research. *Strategic Management Journal*, 8(4), 403-410.

MIT (2021). Capitalizing on the data economy. MIT Technology Review Insights, 10 p. Retrieved from https://wp.technologyreview.com/wp-content/uploads/2021/12/Capitalizing-on-the-data-economy_121521.pdf

Nahr, N., & Heikkilä, M. (2022). Uncovering the identity of Electronic Markets research through text mining techniques. *Electronic Markets*, 32(3), 1257-1277.

Oliveira, M. I. S., & Lóscio, B. F. (2018). What is a data ecosystem?. In Proceedings of the 19th Annual International Conference on Digital Government Research: Governance in the Data Age, pp.1-9.

Oliveira, M. I S., Barros Lima, G. D. F., & Farias Lóscio, B. (2019). Investigations into data ecosystems: a systematic mapping study. *Knowledge and Information Systems*, 61, 589-630.

Osterwalder, A., Pigneur, Y, & Tucci, C. (2005). Clarifying Business Models: Origins, Present, and Future of the Concept, *Communications of the Association for Information Systems*. 16(1), DOI: 10.17705/1CAIS.01601 Available at: https://aisel.aisnet.org/cais/vol16/iss1/1

Osterwalder, A., & Pigneur, Y. (2010). Business Model Generation: A Handbook for Visionaries, Game Changers, and Challengers. Wiley

Otto, B. & Jarke, M. (2019). Designing a multi-sided data platform: findings from the International Data Spaces case. *Electronic Markets*, 29, 561–580. https://doi.org/10.1007/s12525-019-00362-x

Parikka, H., Härkönen, T. & Sinipuro, J. (2021). A fair data economy is built upon collaboration, Sitra studies 191, June 2021, Retrieved from: https://www.sitra.fi/en/publications/a-fair-data-economy-is-built-upon-collaboration

Pohle, G. & Chapman, M. (2006). IBM's global CEO report 2006: business model innovation matters, *Strategy & Leadership*, 34(5), pp. 34-40.

Pucihar, A. (2020). The digital transformation journey: Content analysis of Electronic Markets articles and Bled eConference proceedings from 2012 to 2019. *Electronic Markets*, 30(1), 29–37. https://doi.org/10.1007/s12525-020-00406-7

Pucihar, A., Lenart, G., Kljajić Borštnar, M., Vidmar, D., & Marolt, M. (2019). Drivers and outcomes of business model innovation—Micro, small and medium-sized enterprises perspective. *Sustainability*, 11(2), 344.

Rantanen, M. M., Hyrynsalmi, S., & Hyrynsalmi, S. M. (2019, June). Towards ethical data ecosystems: A literature study. In 2019 IEEE International Conference on Engineering, Technology and Innovation (ICE/ITMC) June, pp. 1-9.

Saaristo, A., & Heikkilä, M. (2022). A fair data-driven economy - The future of Europe, CCR Insights 2/2022, Turku School of Economics, Retrieved from: https://www.utu.fi/sites/default/files/public%3A//media/file/ccr_insights_2_2022_afairdatadriveneconomy_thefutureofeurope_v3_saavutettava%281%29.pdf

Saebi, T., Lien, L. and Foss, N. J. (2017) What drives business model adaptation? The impact of opportunities, threats and strategic orientation. *Long Range Planning*, 50 (5), pp. 567-581.

Seppälä, A., Birkstedt, T., & Mäntymäki, M. (2021). From ethical AI principles to governed AI. In Proceedings of the 42nd International Conference on Information Systems (ICIS2021).

Sitra (2021). Raw data (excel). Retrieved from : https://www.sitra.fi/en/publications/the-future-of-european-companies-in-data-economy-2021/

Soluk, J., Miroshnychenko, I., Kammerlander, N., & De Massis, A. (2021). Family influence and digital business model innovation: the enabling role of dynamic capabilities. *Entrepreneurship Theory and Practice*, 45(4), 867-905.

Spieth, P., & Schneider, S. (2016). Business model innovativeness: designing a formative measure for business model innovation. *Journal of business Economics*, 86, 671-696.

Strauch, M., Pidun, U., & zu Knyphausen-Aufseß, D. (2019). Process matters–How strategic decision-making process characteristics impact capital allocation efficiency. *Long Range Planning*, 52(2), 202-220.

Teece, D.J., (2010). Business models, business strategy and innovation. *Long Range Plan*ning. 43 (2–3), 172–194. https://doi.org/10.1016/j.lrp.2009.07.003.

Trabucchi, D. and Buganza, T. (2019). Data-driven innovation: switching the perspective on Big Data. *European Journal of Innovation Management*, 22(1), 23-40. https://doi.org/10.1108/EJIM-01-2018-0017

Ulander, M.; Vierula, T.; Ahomäki, M.; Kultanen, H. & Polifke, A. (2021). The Future of European Companies in Data Economy. Sitra. https://www.sitra.fi/en/publications/the-future-of-european-companies-in-data-economy-2021/

Vermanen, M., Rantanen, M.M., Koskinen, J. (2022). Privacy in Internet of Things Ecosystems – Prerequisite for the Ethical Data Collection and Use by Companies. In: Kreps, D., Davison, R., Komukai, T., Ishii, K. (eds) Human Choice and Digital by Default: Autonomy vs Digital Determination. HCC 2022. IFIP Advances in Information and Communication Technology, vol 656. Springer, Cham. https://doi.org/10.1007/978-3-031-15688-5_2

Wong, K. K. K. (2013). Partial least squares structural equation modeling (PLS-SEM) techniques using SmartPLS. *Marketing Bulletin*, 24(1), 1-32.

Zuboff, S. (2019). Surveillance capitalism and the challenge of collective action. In New labor forum, 28(1), pp. 10-29). Sage CA: Los Angeles, CA: SAGE Publications.

Appendix

Constructs and items

Construct	*Item*
Potential Benefit from data	**How much potential you see in the data economy to… (Scale: 1 = Strongly disagree...5 = Strongly agree)**
Item 1	Create additional revenue from current business model?
Item 2	Create new revenue streams from innovations
Item 3	Saving costs
BM change	**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)**
Item 1	Customers (Example: Traditionally we have been B2B company only but now we also/only have consumer customers.)
Item 2	Channels (Example: Traditionally we have sold our products through wholesalers but we have now opened up e-commerce site for direct access.)
Item 3	Value proposition (Example: Previously we have sold products but now we offer services where our own and others´ products are part of.)
Item 4	Activities (Example: We have stopped or started new activities - previously we have been purely a hardware company but now we have software coding also.)
Item 5	Resources (Example: We have acquired new or discarded old resources (factories, people, skills).)
Item 6	Partners (Example: We have new partners helping us in creation and production of our value proposition to our customers, e.g. offshoring, near-shoring.)
Item 7	Revenue models (Example: From one-off transactions to time-based subscription.)
Data ecosystem participation	**How well do the following statements describe the current status of your company? (Scale: 1 = does not describe at all ... 5 = describes very well)**
Item 1	Our company is part of one or more data ecosystems

Construct	*Item*
Item 2	We are planning to facilitate data ecosystems
Item 3	Our company is the facilitator of one or more data ecosystems
Fair & sustainable data usage practices	**Please indicate whether the following objectives of data use are taken into practice in your company (Scale: 1 = totally disagree ... 5 = totally agree)**
Item 1	We offer our customers easy tools to access and manage their personal and/or business data
Item 2	We communicate about the use of data in our corporate social responsibility reporting
Item 3	Data we gather from consumers is available for them to use in other services outside our company
Item 4	We have defined ethical rules for our organization for using, collecting and sharing data
Item 5	We strive to create trust by acting and behaving transparently
Item 6	Our digital services are designed to respect privacy
Item 7	Our digital services are designed to respect control over personal and business data
Item 8	Company's consideration of the rights of individuals and/or organizations exceeds statutory requirements
Data-driven innovation	**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)**
Item 1	In product development, we primarily invest in continuous and gradual improvements in our products.
Item 2	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.
Item 3	We continuously invest in the innovation of new products / services
Item 4	We create value from data, not just for our operations, but also for society, people, and environment.