systems

MDPI

Article

Data-Driven Business Model Innovation in Europe: Ethical Data Practices and Ecosystem Involvement

Marikka Heikkilä *, Jukka Heikkilä and Farhan Ahmad

School of Economics, University of Turku, 20014 Turku, Finland; jups@utu.fi (J.H.); farhan.ahmad@utu.fi (F.A.)
* Correspondence: marikka.heikkila@utu.fi

Abstract: Creating, sharing, and using data are expected to lead to the development of new innovative business models. This study investigates the interplay between business model change, ethical data practices, and participation in data ecosystems in fostering data-driven innovation. Using survey data from 1200 European companies, analyzed through partial least squares structural equation modeling (PLS-SEM), the findings reveal that while firms recognize the potential benefits of data, business model change alone is insufficient to drive innovation. Instead, active engagement in data ecosystems and adherence to ethical data practices together have a significant positive impact on data-driven innovation. This research contributes to the business model innovation literature by highlighting the role of ecosystems and ethical governance in shaping sustainable data-driven innovations. This study also provides practical insights for firms seeking to transition toward more collaborative and ethically grounded data-driven business models.

Keywords: business model innovation; data-driven innovation; data ecosystems; ethical data practices

check for updates

Academic Editors: Claudia Covucci and Maria Giovanna Confetto

Received: 12 January 2025
Revised: 18 February 2025
Accepted: 23 February 2025
Published: 27 February 2025

Citation: Heikkilä, M.; Heikkilä, J.; Ahmad, F. Data-Driven Business Model Innovation in Europe: Ethical Data Practices and Ecosystem Involvement. *Systems* **2025**, *13*, 164. https://doi.org/10.3390/systems13030164

1. Introduction

The global economy heavily relies on data as a multifaceted asset. Creating, sharing, and using data are expected to lead to innovative new business models (BMs) [1]. According to the European Commission [2], data-driven innovations are anticipated to be crucial in enhancing productivity and resource efficiency. Companies can leverage digitalization and big data analytics to transform their BMs, as indicated by [3–6]. Research shows that a company's data analytics capabilities drive BM innovation [4–8] and that a data-driven BM impacts a firm's performance [5].

Recent research especially within the Industry 4.0 context suggests that innovative companies need to invest efforts in creating and participating in data ecosystems [9–12]. By engaging in these ecosystems, companies gain access to a broader range of data sources and collaborative opportunities. This ensures they stay up to date with the latest industry trends and technological advances [13]. Reinforcing this notion, the European data strategy aims to position the EU as a leader in a data-driven society by fostering the development of data ecosystems. EU has strongly supported the creation of data ecosystems, or data spaces, between trusted partners where businesses have easy access to high-quality industrial data, boosting growth and creating new BMs and value [2,14].

However, the European data strategy [15] also includes strong regulations and rules for storing and sharing data to ensure that personal and sensitive business data are secure. Also, the research literature consistently underscores the necessity of proper data-handling practices [16]. Factors such as low-quality data, unclear ownership, and ambiguous usage rights have been recognized as significant impediments to data-driven business [17–20]. While regulations play a pivotal role in safeguarding against improper data use and potential violations of privacy and trade secrets [21,22], they can also serve as obstacles to the innovation of new data-driven BMs [23–25]. Taken together, these findings underscore the importance of ethical data practices in innovating data-driven business [26,27].

While research on data-driven BMs has expanded, critical gaps remain in understanding how three interconnected factors—BM change, ethical data practices, and ecosystem participation—contribute to successful data-driven innovation. The current literature emphasizes technological capabilities [4] and organizational data competencies [5–8], with limited exploration of ecosystem co-creation potential [28]. However, the complex interplay between ecosystem engagement, ethical data governance, and BM change in driving data-driven innovation remains understudied. This research addresses this gap by examining how these factors collectively enable data-driven innovation and foster responsible business practices. Using structural equation modeling (PLS-SEM) on data from 1200 European companies, we investigate the following question: "How do potential benefits from data drive BM change and data ecosystem participation, ultimately enabling data-driven innovation through ethical data practices?"

This study contributes to the literature on BM innovation by highlighting the significance of data ecosystems that promote the ethical use of data when introducing data-driven innovations [28,29].

The structure of this paper is laid out as follows: We begin with a theoretical framework elaborating on the formulation of the research hypotheses and the research model. Subsequently, we provide an in-depth analysis of the data, covering aspects like the model's validity and reliability, as well as the conceptual framework. Finally, we engage in a discussion of our findings. We conclude by showing that when introducing new data-driven innovations, companies should change their BMs but also take part in data ecosystems that make it easier to adopt ethical data practices. This paper concludes with a discussion of the limitations of this study and suggestions for future research.

2. Theoretical Framework

2.1. BM Changes and Business Potential

A BM consists of key components such as customer segments, revenue streams, costs, resources and tasks, partners, and distribution channels, and provides a framework for understanding how these elements interact within the overall business structure [29–32]. From an architectural perspective, a BM defines the processes involved in creating and delivering a specific value proposition to both existing and potential customers, as well as the mechanisms through which a company captures the value it generates [6,30].

BMs are structured upon three interdependent dimensions: value proposition, value creation, and value capture. These dimensions constitute a comprehensive framework through which organizations conceptualize, implement, and monetize their strategic initiatives [33]. The value proposition dimension encompasses an organization's offering to its target market segments. This proposition delineates specific products, services, and solutions designed to address identified market needs while adhering to stakeholder expectations. Value propositions may generate multifaceted benefits, incorporating economic returns, social impact, and environmental sustainability considerations [34–36]. Value creation, in turn, involves the processes and activities through which a company develops its value proposition and delivers it to customers. It requires the integration of resources, capabilities, and partnerships to produce offerings for the customer [37]. Last, value capture pertains to the mechanisms a company employs to retain a portion of the value it has created, thereby generating revenue and profit. It involves setting appropriate pricing strategies, cost structures, and revenue models that ensure the company can sustain its operations and achieve financial objectives [29,38,39].

BMs are not static, but companies may evolve their models to respond to changing market demands or pursue new growth opportunities [40–45]. Such modifications can vary from minor tweaks in specific components of the BM to a comprehensive transformation of the whole framework [46,47].

A data-driven BM is defined as a BM where data are a core component [29]. Data can be utilized in several components of the data-driven BM: data can be a key resource, data analytics can be the key activity to generate customer value, or data or information can be integrated into the value proposition [48,49]. Data-driven BMs have increasingly been noted as a means to enhance business competitiveness [50]. It has been most visible in the consumer market [51], but the continual digital transformation in the industrial sector, commonly referred to as "Industry 4.0", also signifies a growing emphasis on data utilization within the industry [20,52].

One of the key drivers of data-driven BMs is the rise of new technologies that enable data collection, storage, and analysis at a massive scale; for instance, research [6] contends that a firm's proficiency in big data analytics has a positive impact on its capacity to innovate its BM. Additionally, according to [4] businesses that proactively utilize social media, big data, and information technology can boost their performance by transforming their BMs and amplifying their innovation potential.

However, the results from capitalizing on these opportunities differ. A classic example is Rolls Royce's "Power by the Hour" service BM for its jet engines [53] and the more recent CHAT GPT [54] shows how data-driven BMs can create value for both businesses and their customers. On the other hand, there are some notorious failures, such as the startup company Cambridge Analytica, which obtained personal data from Facebook without user consent and used these data to target political ads [55]. The above examples verify how expectations from data utilization do not automatically translate into successful innovation.

Research shows that companies often modify their BMs to meet strategic objectives like boosting profitability, business expansion, or penetrating new markets [56]. As such, if a firm recognizes the potential advantages that data can offer, it would be incentivized to alter its BM to capitalize on these benefits [40–43,57,58].

In summary, the literature suggests that companies that leverage data can enhance their performance and innovation capacity by transforming their BMs. Changes to BMs are driven by the prospective advantages of enhancing profitability, growing existing operations, or breaking into new markets. Thus, the following hypothesis is proposed:

H1. *Potential benefits from data are positively related to BM change (see Figure 1).*

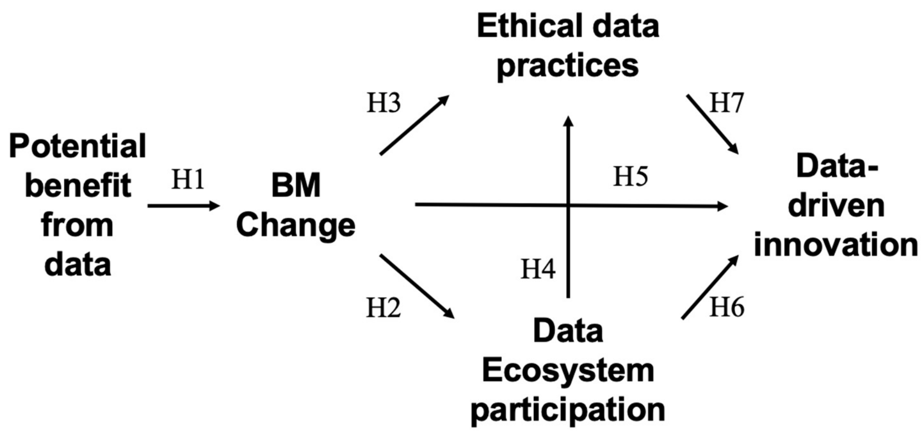

Figure 1. The research model.

2.2. Data Ecosystems

Data-driven innovation often requires capabilities beyond individual organizations. Data ecosystems enable multiple entities—including companies, government agencies, and stakeholders—to collaboratively exchange and utilize data [11,13,59–61]. Through these ecosystems, organizations access diverse data sources and shared knowledge to develop innovative solutions [59–62].

Platform-based ecosystems facilitate structured data exchange between participants [62] while emerging public data spaces operate independently of single commercial entities. The European GAIA-X initiative, led by the International Data Spaces Association, exemplifies this trend, providing a federated infrastructure governed by European data protection standards [14]. This infrastructure enables both private and public organizations to enhance their data-driven BMs through external data integration.

Research on data ecosystems encompasses several dimensions: definitions and taxonomies [61,62], technical architecture [13], governance mechanisms addressing trust, data rights, and coordination [20,63,64], and value [28,65–67]. Recent studies highlight ecosystem participation's strategic importance, with approximately one-third of organizations actively engaging in data-sharing partnerships [66]. This trend suggests that as companies modify their BMs to leverage data assets, they increasingly participate in ecosystem collaborations to access complementary capabilities and resources.

H2. *BM changes are positively related to participation in data ecosystems.*

2.3. Ethical Use of Data

The literature indicates that numerous companies continue to ground their innovation processes in a non-digital past [63]. For innovation to effectively derive from data, several modifications in companies' innovation activities are needed, including support from senior management and the cultivation of an organizational culture with a focus on data. Ethical data practices refer to the fair and responsible handling of personal and business data by organizations. These practices ensure that data are collected, analyzed, and shared in a way that is secure, transparent, and respects the privacy and rights of individuals and businesses [64]. For example, the General Data Protection Regulation requires organizations to safeguard personal data and respect the privacy rights of individuals within the EU. Thus, companies could be held accountable for actions that breach their customers' privacy, especially when processing data for purposes not explicitly approved by their customers, presenting a potential risk—and this risk amplifies if companies share data with business ecosystem partners and subsequently cede some control over that data [68]. This requires even more emphasis on ethical data practices.

Therefore, scholars emphasize that mere adherence to legal mandates is not enough. Explicit processes and approaches need to be implemented to champion ethical data practices [69]. Ethical data practices involve using data in ways that create social, environmental, and economic value while minimizing negative impacts on society and the environment [66]. Moreover, companies need to adhere to intellectual property, copyright, and non-disclosure obligations. Some examples are provided in the Table 1. below.

These practices are to ensure that data are handled in a responsible and fair manner, which helps to build trust with customers and other stakeholders. Thus, we hypothesize the following:

H3. *BM changes are positively related to ethical data practices.*

Table 1. Ethical data practices.

Practice	Description
Privacy	Allowing users to control the terms under which their personal data are acquired and used [70].
Data security	Protecting data by implementing strong data encryption and secure data storage protocols [71].
Ethical code of conduct	Implementing ethical codes of conduct for data collection, use, and sharing, and enforcing penalties for violations [72].
Transparency	Being transparent about data collection and use practices and providing regular updates to customers and stakeholders [73,74].
Data sovereignty	Ensuring that individuals and businesses have control over their data, such as giving users the ability to opt in or opt out of certain data processing activities [75] and allowing them to easily access, manage, and delete their personal data [76].
Portability	If the user wishes to do so, allow the data to be used in other services outside our company [21].
Consideration of rights	Consideration of rights beyond the legal minimum (e.g., GDPR, Data Act, Data Governance Act), such as prohibiting harassment on social media platforms [77].
CSR	Incorporating data privacy and security practices into corporate social responsibility (CSR) reporting [78]. CSR communicates data practices for stakeholders [79].

Furthermore, the literature suggests that participating in data ecosystems has an impact on the adoption of ethical data practices [80,81]. This is because data ecosystems facilitate knowledge sharing and collaborative learning. Organizations can learn from each other's experiences, mistakes, and best practices, leading to the collective adoption of more ethical data practices. It often agrees on shared standards and best practices for data handling, use, and sharing [59,61]. Data ecosystems, such as GAIA-X promote the use of shared technologies and tools that are designed with ethical considerations in mind [14]. The inherent transparency in such systems encourages ethical data handling since any misuse can be more easily identified and traced back. Thus, we hypothesize the following:

H4. *Participation in data ecosystems is positively related to ethical data practices.*

2.4. Data-Driven Innovation

According to the existing literature, data-driven innovation is defined as business innovation that leverages data and has the potential to create both positive economic and social outcomes [29]. Innovative firms continuously invest in processes that help them introduce new products and services to the market. Through gathering and analyzing data from diverse sources, a company can discern how customers perceive the value of its offerings. This understanding can further guide the company in innovating ways to deliver even greater value to the market. The previous literature suggests that instead of introducing radical innovations at once, the companies should experiment with smaller changes in their BMs first, thus learning while reconfiguring [82]. As an example, a change in a BM to a more customer-centric approach can facilitate data-driven innovation by enabling the company to better understand its customers' needs and preferences and to develop innovative solutions that address these needs [83]. Therefore, we examined whether changes to BMs increase data-driven innovation with the following hypothesis:

H5. *BM changes are positively related to data-driven innovation.*

The literature also suggests that participation in data ecosystems can enhance data-driven innovation for several reasons: ecosystems consisting of various stakeholders help to access diverse data that can provide new insights and perspectives, which is critical for innovation [13]. They facilitate collaboration and knowledge sharing among participants. Such a cooperative setting promotes the sharing of ideas, optimal practices, and novel methodologies for data gathering and utilization, which in turn amplifies data-driven innovation [84]. Data ecosystems often involve the use of advanced tools and technologies for data collection, processing, and analysis [61]. Participating in such ecosystems allows firms to access and leverage these tools and technologies, thereby enhancing their data-driven innovation capabilities. Therefore, we propose the following hypothesis:

H6. *Participation in data ecosystems is positively related to data-driven innovation.*

Ethical data practices are expected to create a foundation of trust among stakeholders [85]. When users, customers, and partners trust that an organization is handling data ethically, they are more inclined to share data, collaborate, and support data-driven initiatives. The higher quality and quantity of data can subsequently fuel more meaningful and innovative insights. Ethical practices often align with current and emerging regulations related to data privacy and usage. Compliance ensures that businesses do not face legal impediments or penalties. Also, by adopting ethical data practices, organizations may avoid potential pitfalls associated with data misuse, such as biases in AI models [86]. By avoiding these pitfalls, organizations can focus their resources and efforts on innovation rather than damage control. Last, organizations recognized for ethical data handling can benefit from positive public perception. This enhanced reputation can attract talent, partners, and customers, all of whom can bring unique perspectives and insights that drive innovation [20].

H7. *Ethical data practices are positively related to data-driven innovation.*

Figure 1 presents the above-hypothesized seven relationships between factors driving data-driven innovation.

3. Methodology

3.1. The Measures

Scholars have crafted a variety of scales to gauge modifications in BMs. Some of these scales concentrate on the scope of BM change, assessing structural and component-level changes [57,58,87–89]. On the other hand, novelty scales quantify the magnitude of shifts within a business or entire industry [44,45,90]. There are also specific scales evaluating the disruptiveness of alterations [91], the uniqueness of digital innovation [92], or the long-term viability of the changes [93]. Many researchers link BM changes to changes in its components, such as value proposition, customer relationships and segmentation, channels, key activities and resources, partners, and the revenue model, which are components included in the BM Canvas [31,32]. The BM Canvas is a tool frequently utilized by both scholars and industry professionals to dissect BMs and their subsequent changes [58]. Notably, Eurostat [94] incorporated a scale for evaluating BM changes in its Community Innovation Survey (CIS). Consequently, our research also evaluates BM changes using seven core components consistent with the BM Canvas framework as established by [31,32].

The potential advantages of data-driven innovations were assessed using three criteria, as outlined by [56]: The respondents were first asked to evaluate the potential of the data economy in boosting revenue from their existing BM. Secondly, they were queried whether they could find new revenue streams from innovations or, thirdly, to save costs. Inquiries about participation in data ecosystems revolved around whether the company played a role as a partner or an orchestrator in data ecosystem(s).

Ethical data practices were assessed using a series of eight questions, which gauged aspects like the presence of an ethical code of conduct, transparency measures, considerations of privacy, and data sovereignty [64,69]. Measurement of data-driven innovation combined two aspects: the company's commitment to continuous improvement and the novelty of products and services, as indicated by [95]. Additionally, questions focused on the utilization of data to elevate the customer experience and the generation of societal, personal, and environmental value [96].

3.2. Survey Administration and Sample and Data Collection

The survey was conducted in four European countries (Finland, France, Germany, and the Netherlands) in 2021. The respondents were managers responsible for their company's strategy, information systems, data, digitalization, marketing, or business development. The respondents had voluntarily signed up and expressed their interest in participating in the survey. Invitations for the survey were sent in stages to tailor data collection based on the response rate of each target group. When receiving invitations, the respondents always had the choice to decide whether they wanted to answer the survey or not and they were compensated for their time, for example, with gift cards or airline miles.

The Finnish Innovation Fund Sitra collected the data, after which it opened the data to researchers [96]. Sitra is a unique fund in Finland with national significance, as it is directly accountable to and reports to the Finnish Parliament. Sitra acts as a promoter of experiments and operating models and as a catalyst for cooperation with the aim of building a fair, sustainable, and inspiring future. Currently, one of its focus areas is the data economy.

Table 2 displays the background details of the participants. The sample was evenly distributed among countries, with each country contributing 300 responses. Within each country, there was nearly an equal representation from large, medium, small, and micro-sized companies, excluding sole proprietors. No particular limits were established for different industry sectors.

Table 2. Respondents' profile.

Variable	Category	%
Country	Finland	25.0
	France	25.0
	Germany	25.0
	The Netherlands	25.0
Firm size (turnover EUR)	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	Professional, scientific, and technological operations	6.5
	Administrative and support services	6.4
	Information and communications	9.8
	Mining and quarrying operations	0.3
	Operations of international organizations and institutions	0.8
	Real estate operations	2.4
	Training	0.5
	Transportation and warehousing	4.3
	Farming, forestry, and fishing industries	1.8
	Hotel and catering	3.3
	Other service operations	16.0
	Finance and insurance	8.0
	Construction	5.5
	Electrical, gas, heat, and ventilation maintenance	1.2
	Arts, entertainment, and leisure	2.3
	Industry	11.3
	Health and social services	8.1
	Wholesale and retail; motor vehicle and motorcycle repairs	6.6
	Water supply, sewerage, waste management, and other sanitation	0.4

Our focus on the data economy's capability to transform BMs is well founded: a significant majority, over 80% of the companies surveyed, anticipated that the data economy could provide them with a competitive advantage [97,98].

The survey data contained a minimal amount of missing entries, constituting less than five percent of the overall dataset values. To address these missing values, we employed the mean imputation method as suggested by [99].

To address the potential common method variance in our study, we conducted Harman's single factor test, which measured both dependent and independent variables simultaneously [100]. The first factor obtained through principal axis factoring explained 35.73 percent of the total variance. As this accounted for a relatively small portion of the variance (less than 70%, as recommended by [100]), it affirms that our dataset does not suffer from a significant common method variance problem.

4. Data Analysis

We applied PLS-SEM, using Smart PLS v.3. Next, we described the internal validity, internal reliability, convergent validity, and discriminant validity.

To evaluate the internal validity of the data, the factor loading was analyzed. Factor loading represents the correlation coefficient for the factor and the variable. For an item, a factor loading of at least 0.60 is recommended [99]. In Table 3, all items exceed the recommended threshold, indicating that the item-to-construct loadings were statistically significant and confirming their uni-dimensionality.

Table 3. Descriptive statistics, convergent validity, internal consistency, and reliability of items.

Construct, Items	Indicator Loadings	T Value	Cronbach's Alpha	Composite Reliability	Average Variance Extracted (AVE)
Potential benefits from data			0.86	0.92	0.79
Add revenue from the current BM	0.90	29.825			
New revenue from innovations	0.91	30.993			
Cost savings	0.85	24.726			
BM Change			0.89	0.91	0.60
Customers	0.74	40.202			
Channels	0.75	48.161			
Value proposition	0.80	62.356			
Activities	0.79	60.695			
Resources	0.76	47.953			
Partners	0.78	56.955			
Revenue models	0.81	69.259			
Data ecosystem participation			0.90	0.94	0.83
Participating in	0.90	59.206			
Taking a more prominent role within	0.91	57.444			
Facilitating	0.92	68.273			
Ethical data practices			0.90	0.92	0.58
Data sovereignty	0.78	29.250			
CSR	0.82	30.592			
Portability	0.74	25.638			
Ethical codes of conduct	0.75	26.224			
Transparency	0.72	20.930			
Privacy	0.73	22.549			
Data security	0.78	25.801			
Consideration of rights	0.73	26.734			
Data-driven innovation			0.74	0.83	0.55
Gradual product improvements	0.71	20.221			
Use several data sources to create the best possible customer experience	0.76	26.809			
Innovate new products/services	0.71	20.495			
Create value from data for many stakeholders	0.77	25.638			

To assess the internal reliability of the latent constructs, Cronbach's alpha is commonly used [101], with a threshold value of 0.70 or higher [99]. All constructs met the recommended value, with the highest alpha of 0.90 and the lowest of 0.74 for data-driven innovation. However, Cronbach's alpha may underestimate internal consistency reliability. The authors of [99] proposed the use of the composite reliability (CR) estimate, with a recommended threshold value of 0.70 or higher. The results indicated that the lowest CR value was for data-driven innovation (0.83) and the highest was for data ecosystem participation (0.94).

To assess convergent validity, we calculated the Average Variance Extracted (AVE), which quantifies the average variance explained by a construct through its indicators compared to the measurement error. A recommended threshold is at least 0.50 [99]. As displayed in Table 3, all constructs surpassed this threshold, with the lowest AVE of 0.55 for data-driven innovation and the highest AVE of 0.83 for data ecosystem participation.

The evaluation of discriminant validity is a fundamental aspect of model assessment, according to [99]. This concept refers to the assurance that a particular measuring construct is distinct and not overlapping with other latent variables within the research model, thereby confirming the focus of interest [99]. The Fornell–Larcker criterion states that the square root of the AVE for a given construct should be greater than the correlation between that construct and any other construct in the model. The results of the Fornell-Larcker assessment, presented in Table 4, demonstrate that all the AVE values meet the necessary criteria, indicating that the constructs are sufficiently differentiated.

Table 4. Correlation among constructs and the square root of the AVE.

	a	b	c	d	e
Potential benefits from data (a)	0.887				
BM change (b)	0.387	0.775			
Data ecosystem participation (c)	0.611	0.428	0.910		
Ethical data practices (d)	0.614	0.326	0.583	0.758	
Data-driven innovation (e)	0.594	0.349	0.515	0.651	0.739

The Heterotrait–Monotrait ratio of correlations (HTMTs) is a statistical method to evaluate discriminant validity, which assesses how well a measure or construct is distinct from others. HTMT involves comparing the correlations among indicators measuring different constructs (heterotrait correlations) with the correlations among indicators measuring the same construct (monotrait correlations). If the heterotrait correlations are significantly higher than the monotrait correlations, it suggests potential issues with discriminant validity. HTMT values typically range from 0 to 1, where 1 implies no discriminant validity, and values closer to 0 indicate better discriminant validity. Researchers often use a threshold of 0.85 as a conservative cutoff point, while a value of 0.90 is considered more liberal [102]. In your study, the HTMT values in Table 5 were all lower than 0.729, which indicates that there were no discernible problems with discriminant validity.

Table 5. Heterotrait–monotrait ratio of correlations (HTMTs).

	BM Change	Data Ecosystem Participation	Potential Benefit from Data	Ethical Data Practices
Data ecosystem participation	0.479			
Potential benefits from data	0.440	0.694		
Ethical data practices	0.352	0.626	0.681	
Data-driven innovation	0.394	0.557	0.693	0.729

Last, our analysis also involved an investigation of common method bias. Ref. [100] (p. 7) suggests that a variance inflation factor (VIF) greater than 3.3 at the factor levels could indicate pathological collinearity and suggest the presence of common method bias in a model. In the present study, all VIF values in the full collinearity test were lower than 3.03 at the factor levels, indicating that the model used in our study was free of common method bias.

5. Results

To assess our hypotheses and undertake path analysis, we made use of structural equation modeling (SEM) through the SmartPLS v.3 software. Our choice of PLS-SEM was influenced by its capability to manage complex and extensive models and its less restrictive assumptions about the data [99].

Path Model Analysis

We examined various models with reversed causal relationships and ultimately settled on a final model. According to our analysis, data-driven innovation was explained by a 46% variance, while BM change, participation in data ecosystems, and practices for ethical data use were each explained by variances of 15%, 18%, and 35%, respectively. To evaluate the model fit, we used the SRMR metric, which measures the discrepancy between the predicted and actual correlation matrices. A value of zero indicates a perfect fit, while a value below 0.08 is generally considered good. In our model, the SRMR value was 0.069, indicating a good fit.

To analyze the relationships between constructs, we employed path coefficients and assessed their significance levels. Additionally, we gauged the effect size using Cohen's f2, which provides a measure of practical significance by quantifying the magnitude of the effect of an exogenous variable on an endogenous variable. Generally, f2 values exceeding 0.02, 0.15, and 0.35 indicate small, moderate, and large effect sizes, respectively. It is worth noting that in management research, discovering large effect sizes is relatively uncommon, as has been observed in previous studies [103,104].

The results presented in Figure 2 affirm the statistical significance of all hypotheses examined in this study:

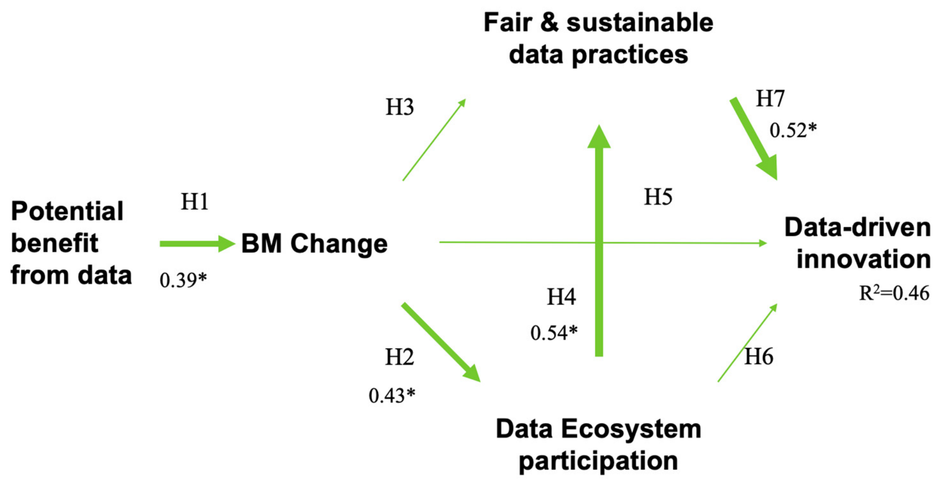

Figure 2. SEM results (* means $p < 0.001$. Thickness of the arrow represents the magnitude of the effect).

Firstly, the results indicate that perceived benefits of the data economy significantly influence BM change (H1: β = 0.39, f2 = 0.18 (moderate effect), $p < 0.001$), suggesting that firms anticipating higher returns from data utilization are more likely to modify their BM. However, while this relationship is statistically significant, the effect size remains moderate, implying that other factors may also be at play in driving BM changes.

Next, BM change demonstrates a moderate effect on data ecosystem participation (H2: β = 0.43, f2 = 0.23 (moderate effect), $p < 0.001$), affirming that firms undergoing BM transformation actively seek collaboration opportunities in data ecosystems.

Participation in data ecosystems strongly influences ethical data practices (H4: β = 0.54, f2 = 0.37 (large effect), $p < 0.001$).

Finally, ethical data practices exhibit a moderate and positive impact on data-driven innovation (H7: β = 0.52, f2 = 0.33 (moderate effect), $p < 0.001$), reinforcing that responsible data governance enhances innovation potential.

While hypotheses H3, H5, and H6 were found to be statistically significant, their Cohen's f2 are small, indicating that they lack practical significance in terms of the magnitude of the effect (H3: β = 0.09, f2 = 0.01, $p < 0.001$; H5: β = 0.11, f2 = 0.02, $p < 0.001$; H6: β = 0.17, f2 = 0.03, $p < 0.001$).

The relationships in Figure 2 are demonstrated to hold true within the specific context of the data economy.

6. Discussion

Our study enriches current innovation research by providing a comprehensive perspective on data-driven innovation in business. It adopts an integrative approach, tying data-driven innovation with the literature on BMs, data ecosystems, and ethical data use. By carrying out PLM-SEM analysis of survey data from 1200 European companies, this research seeks answers to the following research question: How do potential benefits from data drive BM change and data ecosystem participation, ultimately enabling data-driven innovation through ethical data practices?

The response to the research question is depicted as a path in Figure 2: if a company perceives benefits from data and changes its BMs, it is more likely to participate in data ecosystems. This, in turn, facilitates the adoption of ethical data practices, ultimately enabling data-driven innovation.

This study's findings advance our understanding of data-driven innovation in several key areas:

First, the research validates the relationship between perceived benefits from the data economy and BM change. Companies that recognize potential advantages—whether in revenue generation, cost savings, or new business opportunities—are substantially more likely to initiate meaningful changes to their BMs. This finding reinforces the existing literature [56], which identified a positive relationship between anticipated benefits and BM modifications and provides new empirical evidence in the specific context of the data economy.

Second, a valuable contribution is the identification of a pathway to data-driven innovation. Rather than treating innovation as a single step, the research reveals an interconnected sequence: companies begin by recognizing potential benefits, which leads them to change their BMs, subsequently increasing their participation in data ecosystems, and finally adopting ethical data practices. This pathway demonstrates that successful data-driven innovation requires a holistic approach rather than isolated initiatives. This discovery substantiates earlier studies [4–9,16,56–58,66], emphasizing the pivotal role of BM changes. Furthermore, the results affirm the European Union's data strategy [15], highlighting the crucial role of data ecosystems in the promotion of ethical data practices within a company's data-driven innovation endeavors [29,105].

Third, participation in data ecosystems is important for data-driven innovations. This theoretical implication is crucial for understanding the dynamic interplay between firms and their external environment in the data economy [106]. It also adds to the research policy discussion on the need to develop data ecosystems further [61,62]. While past data governance research mainly focused on internal practices [106], our findings on the importance of data ecosystems point out the need for a broader research perspective for holistic governance.

Fourth, this study's emphasis on ethical data practices represents another significant contribution. The findings confirm that ethical considerations are needed for successful innovation [69–75]. This challenges the notion that ethical data practices might constrain innovation, instead suggesting they are enablers of it. The research shows that ethical data practices are intertwined with employees' abilities to create value from data-driven BMs, highlighting the human element in responsible data utilization [107]. Further, it confirms the essential role of data governance provided in data ecosystems [84]. The findings also underscore the growing urgency for more research and the development of information systems methodologies, tools, and data practices founded on ethical principles, as previously highlighted in studies such as [108–110]. This necessity is becoming increasingly critical in the context of artificial intelligence and machine learning [111].

6.1. The Managerial Implications

The managerial implications drawn from these findings suggest that companies aspiring to harness the benefits of the data economy through data-driven innovations should consider the following actions:

a. Modify BMs: The research reveals a clear correlation between the perceived benefits from the data economy and changes in BMs. For managers, this underscores the significance of recognizing the transformative potential of data. It is not enough to merely adjust the BM; the changes must be informed and strategic. BM tools—such as https://businessmakeover.eu/ (accessed on 22 February 2025) and the data-driven services card game [112]—can assist in defining necessary BM changes.

b. Participate in Data Ecosystems: These can be smaller local, national, or European industry-specific innovation ecosystems and data spaces (such as GAIA-X) that encourage companies to collaborate and co-create data-driven services. Such ecosystems offer opportunities not only for sharing experiences but also for open data exchange among partners. They may provide reference architectures and interfaces for data assets while respecting privacy and intellectual property protection.

c. Implement and Communicate Ethical Data Practices: Integrating ethical data practices into daily operations is essential, but equally important is communicating these practices effectively to stakeholders through diverse channels [113]. This is particularly vital as younger generations, who are increasingly aware of sustainability and ethical issues, place higher expectations on organizations to act responsibly.

d. Risk Mitigation through "Sandboxed" Approaches: Companies should consider adopting a "sandboxed" environment, where data-driven innovations can be tested without risk to real-world data or operations. This ensures that all potential solutions are vetted for ethical considerations and compliance before they are rolled out at scale.

6.2. Limitations and Future Research Directions

While this study provides valuable insights into data-driven innovation, several limitations must be acknowledged to ensure a balanced interpretation of the findings. This study relies on self-reported survey responses, which may introduce measurement bias, as participants might overestimate their level of engagement in data-driven practices or ethical data governance. Additionally, while structural equation modeling (SEM) is a powerful analytical tool, it has inherent limitations in establishing causal relationships. The identified pathway to data-driven innovation—from benefit recognition through BM changes to ecosystem participation and ethical practices—suggests a linear progression. However, this linearity may oversimplify the complex, iterative nature of organizational transformation. This study does not fully account for how companies handle setbacks, reversals, or non-linear progressions in this process. As a result, the relationships identified should be interpreted with caution.

Since the data were collected from four European countries, the findings may not be generalizable to other regions with different regulatory environments and technological adoption rates. Replicating this study in other economic regions (e.g., North America, Asia, or emerging markets) or comparing different economic blocs could provide a richer understanding of how institutional and economic contexts shape data-driven innovation. Moreover, future research should examine how multinational companies can effectively promote ethical data usage across diverse regulatory environments.

Although the substantial sample size is expected to mitigate some biases, innovation and ecosystem development are inherently dynamic processes, and capturing them at a single point in time may overlook crucial evolutionary aspects. Since data ecosystems continuously evolve due to technological and market shifts [60], future research could incorporate longitudinal analysis to track these changes over time [89]. Further studies should investigate how participation in data ecosystems facilitates the development of data-driven services, as ecosystems play a crucial role in fostering collective intelligence and supporting the introduction of innovative business concepts. However, the priorities and structures of these ecosystems can differ [114], making it valuable to explore what capabilities are needed to create value with data-driven BMs [20].

Future research should explore alternative structural models, particularly those incorporating mediation effects. For example, digital maturity or industrial sector differences could mediate the relationship between BM changes and data-driven innovation, providing deeper insights into the conditions under which BM change leads to innovation success. Digitally mature organizations have improved digital infrastructure and skills and established innovation support processes that can accelerate the integration of data-driven initiatives into innovation efforts [115]. Similarly, different industries have different levels of stability, competition, digitalization, and regulatory constraints, which can affect a firm's ability to participate and invest resources in data-driven initiatives and the resulting innovation [116]. Due to data limitations and the refined scope of this study, the current study excludes these contextual variables from the analysis. The current survey did not include information on companies' digital maturity, and similarly, industry segmentation was not possible due to the uneven representation of different industries in our sample. In addition, the inclusion of these variables would have increased the complexity of the model and required a large sample size to ensure statistical robustness. The primary focus of this study was on the direct relationships between BM change, ethical data practices, data ecosystem participation, and innovation, so it was necessary to leave certain contextual variables for further research [117].

Alternative methodological approaches—such as case studies, longitudinal studies, in-depth qualitative research, or experimental designs—as well as the use of secondary data sources, such as financial reports or patents, could provide a more nuanced perspective on how firms implement BM changes and innovate with data, as well as help uncover context-specific challenges and best practices for navigating data ecosystems and ethical data practices. For instance, Ref. [118] conducted in-depth qualitative research identifying four major challenges in data-driven BM innovation: data-related issues such as availability, quality, and integration; technology-related difficulties in adopting and integrating new solutions; organizational resistance to change; and regulatory hurdles related to compliance with evolving data protection laws. To address these challenges, they propose engaging in data-driven business ecosystems that facilitate successful business operations. In turn, Ref. [119] provided insights into the interplay between BMs and ethical data practices by examining the user agreements of seven digital platforms. The study illustrated how these platforms leverage consumer data to enhance customer experience and generate revenue while addressing privacy concerns. Moreover, Ref. [120] applied a maturity model in two manufacturing firms, revealing distinct transformation approaches: one prioritizing data capabilities before BM innovation ("data first") and the other focusing on business changes before data enhancement ("business first"). Their findings emphasize the importance of aligning business and technology capabilities to support successful transformation. In a similar vein, a multiple case study [20] of six industrial companies—combining interviews with secondary documents—found that successful data-driven innovation requires not only technical expertise but also cooperation across different departments, such as marketing, R&D, and operations. This provided companies with a more comprehensive understanding of customer needs and market trends, which is crucial for developing innovative solutions.

In conclusion, while this study increases our understanding of the interplay between BM change, data ecosystems, and ethical governance, future research should explore these dimensions in greater depth with multiple methods. This would enhance the robustness, applicability, and generalizability of the findings across different industries and regulatory environments.

7. Conclusions

This research contributes to the literature on data-driven innovation. The findings demonstrate that successful data-driven innovation requires a comprehensive approach incorporating BM change, ecosystem participation, and ethical data practices. The identified pathway from perceiving benefits to achieving innovation provides a practical framework for companies seeking to leverage data effectively.

This study supports the European Union's data strategy, particularly in highlighting the crucial role of data ecosystems in promoting ethical data practices. It shows that companies cannot achieve meaningful data-driven innovation in isolation; instead, they must actively engage with broader ecosystems while maintaining strong ethical standards.

For practitioners, these findings suggest the need for a strategic approach to data innovation that includes thoughtful BM modifications, active participation in data ecosystems, and robust ethical data practices. The research also emphasizes the importance of viewing ethical considerations not as constraints but as enablers of innovation.

Looking forward, while this research provides valuable insights, it also highlights the need for further investigation into several areas. Future studies should explore these relationships in different geographical contexts, examine the temporal dynamics of data ecosystems, and investigate the specific mechanisms through which companies create and capture value from data-driven BMs. Such research would further enhance our understanding of how organizations can successfully navigate the evolving landscape of data-driven innovation while maintaining ethical standards and fostering productive ecosystem relationships.

Author Contributions: Conceptualization, M.H.; methodology, F.A.; validation, J.H.; formal analysis, M.H.; writing—original draft preparation, M.H.; writing—review and editing, M.H. and J.H. The article is an expanded version of a conference article [121]. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: The raw data are available in Excel form at https://www.sitra.fi/en/publications/the-future-of-european-companies-in-data-economy-2021/ (accessed on 22 February 2025).

Acknowledgments: We are grateful to The Finnish Innovation Fund Sitra for making the data available.

Conflicts of Interest: The authors declare no conflicts of interest.

References

1. Brynjolfsson, E.; Hitt, L.; Kim, H. Strength in numbers: How does data-driven decision making affect firm performance? *SSRN Electron. J.* **2011**. Available online: https://ssrn.com/abstract=1819486 (accessed on 22 February 2025). [CrossRef]
2. Available online: https://aisel.aisnet.org/icis2011/proceedings/economicvalueIS/13 (accessed on 22 February 2025).
3. European Commission. *Towards a European Strategy on Business-To-Government Data Sharing for the Public Interest: Final Report Prepared by the High-Level Expert Group on Business-To-Government Data Sharing*; Publications Office of the European Union: Luxembourg, 2021. [CrossRef]
4. Bouwman, H.; de Reuver, M.; Nikou, S. The impact of Digitalization on Business models: How IT Artefacts, Social Media, and Big Data Force Firms to Innovate Their Business model. In Proceedings of the 14th Asia-Pacific Regional Conference of the International Telecommunications Society (ITS): "Mapping ICT into Transformation for the Next Information Society", Kyoto, Japan, 24–27 June 2017. Available online: https://hdl.handle.net/10419/168475 (accessed on 22 February 2025).
5. Bouwman, H.; Nikou, S.; de Reuver, M. Digitalization, business models, and SMEs: How do business model innovation practices improve performance of digitalizing SMEs? *Telecommun. Policy* **2019**, *43*, 101828. [CrossRef]
6. Ciampi, F.; Demi, S.; Magrini, A.; Marzi, G.; Papa, A. Exploring the impact of big data analytics capabilities on business model innovation: The mediating role of entrepreneurial orientation. *J. Bus. Res.* **2021**, *123*, 1–13. [CrossRef]
7. Troisi, O.; Visvizi, A.; Grimaldi, M. Digitalizing Business Models in Hospitality Ecosystems: Toward Data-Driven Innovation. *Eur. J. Innov. Manag.* **2023**, *26*, 242–277. [CrossRef]
8. Bhatti, S.H.; Santoro, G.; Khan, J.; Rizzato, F. Antecedents and consequences of business model innovation in the IT industry. *J. Bus. Res.* **2021**, *123*, 389–400. [CrossRef]
9. Azkan, C.; Möller, F.; Ebel, M.; Iqbal, T.; Otto, B.; Poeppelbuss, J. Hunting the Treasure: Modeling Data Ecosystem Value Co-Creation. In Proceedings of the Forty-Third International Conference on Information Systems, Copenhagen, Denmark, 9–14 December 2022.
10. Hubaux, J.P.; Juels, A. Privacy is dead, long live privacy. *Commun. ACM* **2016**, *59*, 39–41. [CrossRef]
11. Jussen, I.; Möller, F.; Schweihoff, J.; Gieß, A.; Giussani, G.; Otto, B. Issues in Inter-Organizational Data Sharing: Findings from Practice and Research Challenges. *Data Knowl. Eng.* **2024**, *150*, 102280. [CrossRef]
12. Ofulue, J.; Benyoucef, M. Data monetization: Insights from a technology-enabled literature review and research agenda. *Manag. Rev. Q.* **2022**, *74*, 521–565. [CrossRef]
13. Oliveira, M.I.S.; Barros Lima, G.D.F.; Farias Lóscio, B. Investigations into data ecosystems: A systematic mapping study. *Knowl. Inf. Syst.* **2019**, *61*, 589–630. [CrossRef]
14. Beverungen, D.; Hess, T.; Köster, A.; Lehrer, C. From private digital platforms to public data spaces: Implications for the digital transformation. *Electron. Mark.* **2022**, *32*, 493–501. [CrossRef]
15. European Commission. *The European Data Strategy*; European Commission: Brussels, Belgium, 2020. Available online: https://ec.europa.eu/commission/presscorner/detail/en/fs_20_283 (accessed on 22 February 2025).
16. Bennett, S. Governance in practice: Big data, privacy and information governance-incorporating an ethical-based assessment. *Govern. Dir.* **2019**, *71*, 244–254.
17. Rantanen, M.M.; Hyrynsalmi, S.; Hyrynsalmi, S.M. Towards ethical data ecosystems: A literature study. In Proceedings of the 2019 IEEE International Conference on Engineering, Technology and Innovation (ICE/ITMC), Valbonne Sophia-Antipolis, France, 17–19 June 2019. [CrossRef]
18. Ermakova, T.; Blume, J.; Fabian, B.; Fomenko, E.; Berlin, M.; Hauswirth, M. Beyond the hype: Why do data-driven projects fail? In Proceedings of the 54th Hawaii International Conference on System Sciences, Kauai, HI, USA, 5 January 2021. Available online: https://scholarspace.manoa.hawaii.edu/bitstream/10125/71237/1/0498.pdf (accessed on 22 February 2025).
19. Lange, H.E.; Drews, P.; Höft, M. Realization of Data-Driven Business Models in Incumbent Companies: An Exploratory Study Based on the Resource-Based View. In Proceedings of the ICIS 2021, Durgapur, India, 24–27 February 2021.
20. Eriksson, T.; Heikkilä, M. Capabilities for data-driven innovation in B2B industrial companies. *Ind. Mark. Manag.* **2023**, *111*, 158–172. [CrossRef]
21. Krämer, J.; Schnurr, D. Big data and digital markets contestability: Theory of harm and data access remedies. *J. Compet. Law Econ.* **2022**, *18*, 255–322. [CrossRef]
22. Data Act. Data Act: Proposal for a Regulation on Harmonised Rules on Fair Access to and Use of Data; European Commission. 2022. Available online: https://digital-strategy.ec.europa.eu/en/library/data-act-proposal-regulation-harmonised-rules-fair-access-and-use-data (accessed on 3 January 2025).

23. Gandhi, R.; Sharma, A.; Mahoney, W.; Sousan, W.; Zhu, Q.; Laplante, P. Dimensions of cyber-attacks: Cultural, social, economic, and political. *IEEE Technol. Soc. Mag.* **2011**, *30*, 28–38. [CrossRef]
24. Zuboff, S. Surveillance capitalism and the challenge of collective action. In *New Labor Forum*; SAGE Publications: Los Angeles, CA, USA, 2019; Volume 28, pp. 10–29.
25. Gawer, A.; Srnicek, N. *Online Platforms: Economic and Societal Effects*; European Parliamentary Research Service: Brussels, Belgium, 2021. Available online: https://www.europarl.europa.eu/RegData/etudes/STUD/2021/656336/EPRS_STU(2021)656336_EN.pdf (accessed on 3 January 2025).
26. Leone, M.I.; Belingheri, P. The relevance of innovation for ethics, responsibility and sustainability. *Ind. Innov.* **2017**, *24*, 437–445. [CrossRef]
27. Perri, A.; Rocha, V. Grand innovation challenges: Celebrating 30 years of Industry and Innovation with a special issue. *Ind. Innov.* **2023**, *31*, 1–15. [CrossRef]
28. Bresciani, S.; Ciampi, F.; Meli, F.; Ferraris, A. Using Big Data for Co-Innovation Processes: Mapping the Field of Data-Driven Innovation, Proposing Theoretical Developments and Providing a Research Agenda. *Int. J. Inf. Manag.* **2021**, *60*, 102347. [CrossRef]
29. Jetzek, T.; Avital, M.; Bjorn-Andersen, N. Data-driven innovation through open government data. *J. Theor. Appl. Electron. Commer. Res.* **2014**, *9*, 15–16. [CrossRef]
30. Teece, D.J. Business models, business strategy and innovation. *Long Range Plan.* **2010**, *43*, 172–194. [CrossRef]
31. Osterwalder, A.; Pigneur, Y.; Tucci, C. Clarifying business models: Origins, present, and future of the concept. *Commun. Assoc. Inf. Syst.* **2005**, *16*, 1. [CrossRef]
32. Osterwalder, A.; Pigneur, Y. *Business Model Generation: A Handbook for Visionaries, Game Changers, and Challengers*; Wiley: Hoboken, NJ, USA, 2010.
33. Fielt, E. Conceptualising business models: Definitions, frameworks and classifications. *J. Bus. Models* **2013**, *1*, 85–105. [CrossRef]
34. Bocken, N.M.P.; Short, S.W.; Rana, P.; Evans, S. A literature and practice review to develop sustainable business model archetypes. *J. Clean. Prod.* **2014**, *65*, 42–56. [CrossRef]
35. Lüdeke-Freund, F.; Gold, S.; Bocken, N.M.P. A review and typology of circular economy business model patterns. *J. Ind. Ecol.* **2019**, *23*, 36–61. [CrossRef]
36. Geissdoerfer, M.; Savaget, P.; Bocken, N.M.P.; Hultink, E.J. The Circular Economy–A new sustainability paradigm? *J. Clean. Prod.* **2017**, *143*, 757–768. [CrossRef]
37. Ranta, V.; Aarikka-Stenroos, L.; Mäkinen, S.J. Creating value in the circular economy: A structured multiple-case analysis of business models. *J. Clean. Prod.* **2018**, *201*, 988–1000. [CrossRef]
38. Amit, R.; Zott, C. Value creation in e-business. *Strateg. Manag. J.* **2001**, *22*, 493–520. [CrossRef]
39. Schürtz, R.; Seebacher, S.; Dorner, R. Capturing value from data: Revenue models for data-driven services. In Proceedings of the 50th Hawaii International Conference on System Sciences, Hilton Waikoloa Village, HI, USA, 4–7 January 2017; pp. 5348–5357. Available online: https://www.researchgate.net/publication/308201149_Capturing_Value_from_Data_Revenue_Models_for_Data-Driven_Services (accessed on 22 February 2025).
40. Pohle, G.; Chapman, M. IBM's Global CEO Report 2006: Business Model Innovation Matters. *Strateg. Leadersh.* **2006**, *34*, 34–40. [CrossRef]
41. Lindgardt, Z.; Reeves, M.; Stalk, G.; Deimler, M.S. *Business Model Innovation, When the Game Gets Tough, Change the Game*; The Boston Consulting Group: Boston, MA, USA, 2009. [CrossRef]
42. Bucherer, E.; Eisert, U.; Gassmann, O. Towards systematic business model innovation: Lessons from product innovation management. *Creat. Innov. Manag.* **2012**, *21*, 183–198. [CrossRef]
43. Hartmann, M.; Oriani, R.; Bateman, H. The Performance Effect of Business Model Innovation: An Empirical Analysis of Pension Funds. In Proceedings of the 35th DRUID Celebration Conference, Barcelona, Spain, 17–19 June 2013. [CrossRef]
44. Marolt, M.; Lenart, G.; Borstnar, M.K.; Vidmar, D.; Pucihar, A. SMEs perspective on business model innovation. In Proceedings of the 31st Bled eConference Digital Transformation—Meeting the Challenges, Bled, Slovenia, 17–20 June 2018. Available online: https://aisel.aisnet.org/bled2018/2 (accessed on 22 February 2025).
45. Pucihar, A.; Lenart, G.; Kljajić Borštnar, M.; Vidmar, D.; Marolt, M. Drivers and outcomes of business model innovation—Micro, small and medium-sized enterprises perspective. *Sustainability* **2019**, *11*, 344. [CrossRef]
46. Saebi, T.; Lien, L.; Foss, N.J. What drives business model adaptation? The impact of opportunities, threats and strategic orientation. *Long Range Plan.* **2017**, *50*, 567–581. [CrossRef]
47. Eriksson, T.; Heikkilä, M.; Nummela, N. Crafting SME business model for international expansion with data-driven services. In *Business Models and Firm Internationalisation*; Nielsen, C., Marinova, S.T., Marinov, M.A., Eds.; Routledge Frontiers in the Development of International Business, Management and Marketing series; Routledge: London, UK, 2022.
48. Hartmann, P.M.; Zaki, M.; Feldmann, N.; Neely, A. Capturing Value from Big Data–A Taxonomy of Data-Driven Business Models Used by Start-Up Firms. *Int. J. Oper. Prod. Manag.* **2016**, *36*, 1382–1406. [CrossRef]

49. Fruhwirth, M.; Ropposch, C.; Pammer-Schindler, V. Supporting Data-Driven Business Model Innovations: A structured literature review on tools and methods. *J. Bus. Models* **2020**, *8*, 7–25. [CrossRef]
50. Sorescu, A. Data-driven business model innovation. *J. Prod. Innov. Manag.* **2017**, *34*, 691–696. [CrossRef]
51. Babu, M.M.; Rahman, M.; Alam, A.; Day, B.L. Exploring big data-driven innovation in the manufacturing sector: Evidence from UK firms. *Ann. Oper. Res.* **2021**, *333*, 689–716. [CrossRef] [PubMed]
52. Kumar, S.; Bhatia, M.S. Environmental dynamism, Industry 4.0, and performance: Mediating role of organizational and technological factors. *Ind. Mark. Manag.* **2021**, *95*, 54–64. [CrossRef]
53. Smith, D.J. Power-by-the-hour: The role of technology in reshaping business strategy at Rolls-Royce. *Technol. Anal. Strateg. Manag.* **2013**, *25*, 987–1007. [CrossRef]
54. Kshetri, N.; Hughes, L.; Slade, E.L.; Jeyaraj, A.; Kar, A.K.; Koohang, A.; Raghavan, V.; Ahuja, M.; Albanna, H.; ahmad Albashrawi, M.; et al. 'So what if ChatGPT wrote it?' Multidisciplinary perspectives on opportunities, challenges, and implications of generative conversational AI for research, practice, and policy. *Int. J. Inf. Manag.* **2023**, *71*, 102642. [CrossRef]
55. Berghel, H. Malice domestic: The Cambridge Analytica dystopia. *Computer* **2018**, *51*, 84–89. [CrossRef]
56. Heikkilä, M.; Bouwman, H.; Heikkilä, J. From strategic goals to business model innovation paths: An exploratory study. *J. Small Bus. Enterp. Dev.* **2018**, *25*, 107–128. [CrossRef]
57. Latifi, M.A.; Bouwman, H.; Nikou, S. ICT-Driven Business Model Innovation in SMEs: The Role of Organizational Capabilities, Firm Size, and Age. In Proceedings of the BLED 2021 Conference, Online, 27–30 June 2021. Available online: https://aisel.aisnet.org/bled2021/37 (accessed on 22 February 2025).
58. Latifi, M.A.; Nikou, S.; Bouwman, H. Business model innovation and firm performance: Exploring causal mechanisms in SMEs. *Technovation* **2021**, *107*, 102274. [CrossRef]
59. Hein, A.; Weking, J.; Schreieck, M.; Wiesche, M.; Böhm, M.; Krcmar, H. Value co-creation practices in business-to-business platform ecosystems. *Electron. Markets* **2019**, *29*, 503–518. [CrossRef]
60. Basole, R.C.; Russell, M.G.; Huhtamäki, J.; Rubens, N.; Still, K.; Park, H. Understanding Business Ecosystem Dynamics: A Data-Driven Approach. *ACM Trans. Manag. Inf. Syst.* **2015**, *6*, 6. [CrossRef]
61. Oliveira, M.I.S.; Lóscio, B.F. What is a data ecosystem? In Proceedings of the 19th Annual International Conference on Digital Government Research: Governance in the Data Age, Delft, The Netherlands, 30 May–1 June 2018; pp. 1–9.
62. Gelhaar, J.; Groß, T.; Otto, B. A Taxonomy for Data Ecosystems. In Proceedings of the 54th Hawaii International Conference on System Sciences, Kauai, HI, USA, 5 January 2021. Available online: http://hdl.handle.net/10125/71359 (accessed on 22 February 2025).
63. Troilo, G.; De Luca, L.M.; Guenzi, P. Linking data-rich environments with service innovation in incumbent firms: A conceptual framework and research propositions. *J. Prod. Innov. Manag.* **2017**, *34*, 617–639. [CrossRef]
64. Parikka, H.; Härkönen, T.; Sinipuro, J. A fair data economy is built upon collaboration. *Sitra Stud.* **2021**, *191*. Available online: https://www.sitra.fi/en/publications/a-fair-data-economy-is-built-upon-collaboration (accessed on 10 February 2025).
65. Battistella, C.; Colucci, K.; De Toni, A.F.; Nonino, F. Methodology of business ecosystems network analysis: A case study in Telecom Italia Future Centre. *Technol. Forecast. Soc. Change* **2013**, *80*, 1194–1210. [CrossRef]
66. MIT. Capitalizing on the data economy. *MIT Technol. Rev. Insights* **2021**. Available online: https://wp.technologyreview.com/wp-content/uploads/2021/12/Capitalizing-on-the-data-economy_121521.pdf (accessed on 22 February 2025).
67. Toorajipour, R.; Oghazi, P.; Palmié, M. Data ecosystem business models: Value propositions and value capture with Artificial Intelligence of Things. *Int. J. Inf. Manag.* **2024**, *78*, 102804. [CrossRef]
68. Schäfer, F.; Gebauer, H.; Gröger, C.; Gassmann, O.; Wortmann, F. Data-driven business and data privacy: Challenges and measures for product-based companies. *Bus. Horiz.* **2023**, *66*, 493–504. [CrossRef]
69. Vermanen, M.; Rantanen, M.M.; Koskinen, J. Privacy in internet of things ecosystems—Prerequisite for the ethical data collection and use by companies. In *Human Choice and Digital by Default: Autonomy vs Digital Determination*; Kreps, D., Davison, R., Komukai, T., Ishii, K., Eds.; Springer: Cham, Switzerland, 2022; pp. 6–56. [CrossRef]
70. Culnan, M.J.; Bies, R.J. Consumer privacy: Balancing economic and justice considerations. *J. Soc. Issues* **2003**, *59*, 323–342. [CrossRef]
71. Yang, P.; Xiong, N.; Ren, J. Data security and privacy protection for cloud storage: A survey. *IEEE Access* **2020**, *8*, 131723–131740. [CrossRef]
72. Loi, M.; Heitz, C.; Ferrario, A.; Schmid, A.; Christen, M. Towards an ethical code for data-based business. In Proceedings of the 2019 6th Swiss Conference on Data Science (SDS), Bern, Switzerland, 14 June 2019; pp. 6–12. [CrossRef]
73. Morey, T.; Forbath, T.; Schoop, A. Customer data: Designing for transparency and trust. *Harv. Bus. Rev.* **2015**, *93*, 96–105.
74. Trabucchi, D.; Patrucco, A.S.; Buganza, T.; Marzi, G. Is transparency the new green? How business model transparency influences digital service adoption. *Technovation* **2023**, *126*, 102803. [CrossRef]
75. Hummel, P.; Braun, M.; Tretter, M.; Dabrock, P. Data sovereignty: A review. *Big Data Soc.* **2021**, *8*, 2053951720982012. [CrossRef]
76. Sørum, H.; Presthus, W. Dude, where's my data? The GDPR in practice, from a consumer's point of view. *Inf. Technol. People* **2021**, *34*, 912–929. [CrossRef]

77. Zwitter, A.; Gstrein, O.J. Big data, privacy and COVID-19—Learning from humanitarian expertise in data protection. *J. Int. Humanit. Action* **2020**, *5*, 1–7. [CrossRef] [PubMed]
78. Allen, A.M.; Peloza, J. Someone to Watch Over Me: The Integration of Privacy and Corporate Social Responsibility. *Bus. Horiz.* **2015**, *58*, 635–642. [CrossRef]
79. Vollero, A.; Conte, F.; Siano, A.; Covucci, C. Corporate social responsibility information and involvement strategies in controversial industries. *Corp. Soc. Responsib. Environ. Manag.* **2019**, *26*, 141–151. [CrossRef]
80. Koskinen, J.; Knaapi-Junnila, S.; Rantanen, M.M. What if we had fair, people-centred data economy ecosystems? In Proceedings of the 2019 IEEE SmartWorld, Ubiquitous Intelligence & Computing, Advanced & Trusted Computing, Scalable Computing & Communications, Cloud & Big Data Computing, Internet of People and Smart City Innovation, Leicester, UK, 19–23 August 2019; pp. 329–334. [CrossRef]
81. Calzada, I.; Almirall, E. Data ecosystems for protecting European citizens' digital rights. *Transform. Gov. People Process Policy* **2020**, *14*, 133–147. [CrossRef]
82. Berends, H.; Smits, A.; Reymen, I.; Podoynitsyna, K. Learning while (re)configuring: Business model innovation processes in established firms. *Strateg. Organ.* **2016**, *14*, 181–219. [CrossRef]
83. Weill, P.; Woerner, S. *What's Your Digital Business Model?: Six Questions to Help You Build the Next-Generation Enterprise*; Harvard Business Review Press: Boston, MA, USA, 2018.
84. Gelhaar, J.; Becker, F.; Groß, T. Characterization of Relationships in Data Ecosystems. In Proceedings of the Conference on Production Systems and Logistics: CPSL 2022, Hannover, Germany, 17–20 May 2022; pp. 370–379. [CrossRef]
85. Asgarinia, H.; Chomczyk Penedo, A.; Esteves, B.; Lewis, D. Who Should I Trust with My Data? Ethical and Legal Challenges for Innovation in New Decentralized Data Management Technologies. *Information* **2023**, *14*, 351. [CrossRef]
86. Yapo, A.; Weiss, J. Ethical implications of bias in machine learning. In Proceedings of the 51st Hawaii International Conference on System Sciences, Hilton Waikoloa Village, HI, USA, 3–6 January 2018. Available online: http://hdl.handle.net/10125/50557 (accessed on 22 February 2025).
87. Foss, N.J.; Saebi, T. Fifteen years of research on business model innovation: How far have we come, and where should we go? *J. Manag.* **2017**, *43*, 200–227. [CrossRef]
88. Spieth, P.; Schneider, S. Business model innovativeness: Designing a formative measure for business model innovation. *J. Bus. Econ.* **2016**, *86*, 671–696. [CrossRef]
89. Menter, M.; Göcke, L.; Zeeb, C.; Clauss, T. Disentangling the complex longitudinal relationships between business model innovation and firm performance. *J. Bus. Res.* **2023**, *168*. [CrossRef]
90. Clauss, T. Measuring business model innovation: Conceptualization, scale development, and proof of performance. *R&D Manag.* **2017**, *47*, 385–403. [CrossRef]
91. Karimi, J.; Walter, Z. Corporate entrepreneurship, disruptive business model innovation adoption, and its performance: The case of the newspaper industry. *Long Range Plan.* **2016**, *49*, 342–360. [CrossRef]
92. Soluk, J.; Miroshnychenko, I.; Kammerlander, N.; De Massis, A. Family influence and digital business model innovation: The enabling role of dynamic capabilities. *Entrep. Theory Pract.* **2021**, *45*, 867–905. [CrossRef]
93. Bashir, M.; Alfalih, A.; Pradhan, S. Sustainable business model innovation: Scale development, validation and proof of performance. *J. Innov. Knowl.* **2022**, *7*, 100243. [CrossRef]
94. Eurostat. *Community Innovation Survey (CIS): Questionnaire Library, QUESTION—Business Model Changes; European Commission*. 2022. Available online: https://ec.europa.eu/eurostat/cache/website/cis/Questions/Question_BUSSMOD.html (accessed on 10 February 2025).
95. Boer, H.; Gertsen, F. From continuous improvement to continuous innovation: A (retro)(per)spective. *Int. J. Technol. Manag.* **2003**, *26*, 805–827. [CrossRef]
96. Sitra. Raw Data (Excel). Sitra. 2021. Available online: https://www.sitra.fi/wp/wp-content/uploads/2021/05/the-future-of-european-companies-in-data-economy-rawdata-2021.xlsx (accessed on 22 February 2025).
97. Saaristo, A.; Heikkilä, M. A Fair Data-Driven Economy—The Future of Europe. *CCR Insights* **2022**, *2*. Available online: https://www.utu.fi/sites/default/files/public://media/file/ccr_insights_2_2022_afairdatadriveneconomy_thefutureofeurope_v3_saavutettava(1).pdf (accessed on 22 February 2025). [CrossRef]
98. Ulander, M.; Vierula, T.; Ahomäki, M.; Kultanen, H.; Polifke, A. The Future of European Companies in Data Economy. *Sitra*, 2021. Available online: https://www.sitra.fi/en/publications/the-future-of-european-companies-in-data-economy-2021/ (accessed on 10 February 2025).
99. Hair, J.F., Jr.; Hult, G.T.M.; Ringle, C.M.; Sarstedt, M. *A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM)*, 3rd ed.; Sage Publications: Thousand Oaks, CA, USA, 2021.
100. Kock, F.; Berbekova, A.; Assaf, A.G. Understanding and managing the threat of common method bias: Detection, prevention, and control. *Tour. Manag.* **2021**, *86*, 104330. [CrossRef]
101. Bryman, A.; Bell, E. *Business Research Methods*, 3rd ed.; Oxford University Press: New York, NY, USA, 2011.

102. Henseler, J.; Ringle, C.M.; Sarstedt, M. A new criterion for assessing discriminant validity in variance-based structural equation modelling. *J. Acad. Mark. Sci.* **2015**, *43*, 115–135. [CrossRef]
103. Mazen, A.M.M.; Hemmasi, M.; Lewis, M.F. Assessment of statistical power in contemporary strategy research. *Strateg. Manag. J.* **1987**, *8*, 403–410. [CrossRef]
104. Strauch, M.; Pidun, U.; zu Knyphausen-Aufseß, D. Process matters—How strategic decision-making process characteristics impact capital allocation efficiency. *Long Range Plann.* **2019**, *52*, 202–220. [CrossRef]
105. Trabucchi, D.; Buganza, T. Data-driven innovation: Switching the perspective on big data. *Eur. J. Innov. Manag.* **2019**, *22*, 23–40. [CrossRef]
106. Lis, D.; Arbter, M.; Spindler, M.; Otto, B. An Investigation of Antecedents for Data Governance Adoption in the Rail Industry—Findings From a Case Study at Thales. *IEEE Trans. Eng. Manag.* **2022**, *70*, 2528–2545. [CrossRef]
107. Förster, M.; Bansemir, B.; Roth, A. Employee Perspectives on Value Realization from Data within Data-Driven Business Models. *Electron. Mark.* **2022**, *32*, 767–806. [CrossRef]
108. Nahr, N.; Heikkilä, M. Uncovering the identity of electronic markets research through text mining techniques. *Electron. Markets* **2022**, *32*, 1257–1277. [CrossRef]
109. Alt, R.; Klein, S. Twenty Years of Electronic Markets Research—Looking Backwards Towards the Future. *Electron. Markets* **2011**, *21*, 41–51. [CrossRef]
110. Pucihar, A. The Digital Transformation Journey: Content Analysis of Electronic Markets Articles and Bled eConference Proceedings from 2012 to 2019. *Electron. Markets* **2020**, *30*, 29–37. [CrossRef]
111. Seppälä, A.; Birkstedt, T.; Mäntymäki, M. From ethical AI principles to governed AI. In Proceedings of the 42nd International Conference on Information Systems (ICIS 2021), Austin, TX, USA, 12–15 December 2021.
112. Breitfuss, G.; Santa-Maria, T.; Fruhwirth, M.; Disch, L. Use Your Data: Design and Evaluation of a Card-Based Ideation Tool for Data-Driven Services. In Proceedings of the Hawaii International Conference on System Sciences, 3 January 2023. Available online: https://scholarspace.manoa.hawaii.edu/items/b3df1410-42f5-4136-ac28-95f934a1a67c (accessed on 3 January 2025).
113. Confetto, M.G.; Covucci, C.; Addeo, F.; Normando, M. Sustainability advocacy antecedents: How social media content influences sustainable behaviours among Generation Z. *J. Consum. Mark.* **2023**, *40*, 758–774. [CrossRef]
114. Elia, G.; Margherita, A.; Passiante, G. Digital entrepreneurship ecosystem: How digital technologies and collective intelligence are reshaping the entrepreneurial process. *Technol. Forecast. Soc. Change* **2020**, *150*, 119791. [CrossRef]
115. Kane, G.C.; Palmer, D.; Nguyen-Phillips, A.; Kiron, D.; Buckley, N. Achieving digital maturity. *MIT Sloan Manag. Rev.* **2017**, *59*, 1. Available online: http://sloanreview.mit.edu/digital2017 (accessed on 18 February 2025).
116. Remane, G.; Hanelt, A.; Wiesboeck, F.; Kolbe, L.M. Digital Maturity in Traditional Industries: An Exploratory Analysis. In Proceedings of the 25th European Conference on Information Systems (ECIS), Guimarães, Portugal, 5–10 June 2017; p. 10. Available online: https://aisel.aisnet.org/ecis2017_rp/10/ (accessed on 18 February 2025).
117. Heikkilä, M.; Heikkilä, J.; Ahmad, F. European Companies' Readiness and Challenges in Data Economy. In *Proceedings of the 37th Bled eConference, Resilience Through Digital Innovation: Enabling the Twin Transition*; University of Maribor University Press: Maribor, Slovenia, 2024; pp. 637–654. [CrossRef]
118. Mosig, T.; Lehmann, C.; Neyer, A.-K. Data-Driven Business Model Innovation: About Barriers and New Perspectives. *Int. J. Innov. Technol. Manag.* **2021**, *18*, 1–32. [CrossRef]
119. Samuelsson, P.; Larson, M.; Davoudi, S. Balancing Value Propositions with Privacy: Exploring Data-Driven Digital Wellness Business Models. In *Service Innovation and Management*; Witell, L., Ed.; Future of Business and Finance; Springer: Cham, Switzerland, 2025; pp. 127–141. Available online: https://link.springer.com/chapter/10.1007/978-3-031-76560-5_10 (accessed on 18 February 2025).
120. Stahl, B.; Häckel, B.; Leuthe, D.; Ritter, C. Data or Business First?—Manufacturers' Transformation Toward Data-driven Business Models. *Schmalenbach J. Bus. Res.* **2023**, *75*, 303–343. [CrossRef]
121. Heikkilä, M.; Ahmad, F.; Heikkilä, J. Unlocking the potential of data-driven business models: An empirical investigation into the role of ecosystems and fair data use. In *Proceedings of the 36th Bled eConference: Digital Economy and Society: The Balancing Act for Digital Innovation in Times of Instability*; University of Maribor University Press: Maribor, Slovenia, 2023; pp. 85–106. Available online: https://dk.um.si/Dokument.php?dn=&id=168294 (accessed on 10 February 2025).