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Strategic Integration of Artificial Intelligence for Sustainable Businesses: Implications for Data Management and Human User Engagement in the Digital Era

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Abstract: This research paper delves into the pivotal role of strategic integration of artificial intelligence (AI) concepts across sustainability efforts in for-profit businesses. As organizations are increasingly starting to rely on AI-driven solutions, this study examines the profound implications of AI integration for two critical facets: impact on data management in companies and diversification of human engagement during interactions in the digital ecosystem. The main goal of this research is to analyze the AI adoption index within a sample of 240 medium and large-sized companies (therefore excluding new companies, small startups, and low-scale AI applications). Firstly, the paper scrutinizes how AI technologies enhance data management by enabling efficient data collection, analysis, and utilization. It emphasizes the importance of AI-driven data analytics in improving decision-making processes, resource optimization, and overall operational efficiency for sustainable practices. Secondly, this research explores how AI-driven personalization, omnichannel interactions, and recommendation systems significantly impact user experiences, satisfaction, and loyalty, ultimately contributing to sustainable business growth. Findings show that there are three separate profiles of companies (low, moderate, and high), distinguished by AI adoption index and other important dimensions. Future research should focus on determining preconditions for successful planning of AI adoption index improvement, using a data-driven approach.

Keywords: sustainable business; artificial intelligence; data management; user engagement

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Citation: Jankovic, S.D.; Curovic, D.M. Strategic Integration of Artificial Intelligence for Sustainable Businesses: Implications for Data Management and Human User Engagement in the Digital Era. *Sustainability* **2023**, *15*, 15208. https://doi.org/10.3390/su152115208

Received: 19 September 2023
Revised: 15 October 2023
Accepted: 21 October 2023
Published: 24 October 2023

1. Introduction

In today's rapidly evolving business landscape, the convergence of artificial intelligence (AI) and sustainability has emerged as a transformative force for medium-sized and large companies in Europe. The strategic integration of AI technologies into sustainability efforts represents a pivotal shift in how organizations tackle environmental, social, and economic challenges. One important fact is that only one in five companies does not plan to invest in AI [1]. Many countries have decided to take a strategic approach to AI development and, so far, more than 30 countries have developed strategies for AI development, with the USA and Western Europe leading the way. Projections for technology growth in the next period outline AI and marketing automation as technologies with the highest potential [2]. In the Balkan region, Serbia is one of the first countries that defined a national strategy for the use of AI until 2025, as one of the main foundations of economic growth and digitalization processes in companies [3]. The integration of AI in sustainability strategies is a response to the complex and interrelated challenges faced by companies in Europe. Medium-sized and large companies are at the forefront of this transition, leveraging AI as a strategic tool to navigate this intricate competitive landscape [4,5]. A study from a Finances online [6] report stated that in 2023, "AI and machine learning are game changers", supporting it with findings that it makes work easier, more efficient, and more sustainable. From the same study, it can be learned that 90% of surveyed business executives expect to fully adopt AI by the year 2027. Sustainability reporting and disclosure have also been significantly impacted by AI integration.

In addition to these tangible applications, AI is nowadays mostly influencing decision-makers in companies, through innovating partial or full automation of business processes, but also through enabling more efficient, "green"-driven marketing efforts. Companies are increasingly relying on AI-powered data analysis to power their strategy, upgrade efficiency internally, and improve client value management. Strategy decision-makers are doing that to ensure that company capital is allocated to projects and initiatives that align with goals that ensure business sustainability. On the other hand, ethical concerns surrounding data protection within AI models, data privacy, and the potential for algorithmic bias must be carefully addressed. Companies must ensure that their AI systems are transparent, fair, and aligned with their strategy pillars and initiatives [7,8]. Cutting-edge research in the field of mathematical modeling and control theory is opening new avenues for understanding and manipulating complex systems, as studied by Ali and Li [9,10]. Moreover, Xua [11] delves into the development of extended hybrid models applied in different industries and sciences. Lastly, Huang [12] explores the intriguing world of neural networks, investigating fractional-order neural networks with multiple delays. These studies collectively underscore horizons of mathematical modeling, offering insights into a diverse range of systems of adopting and implementing AI.

Two assumptions remain unclear or totally unknown after analysis of the existing literature; the first presents a dilemma regarding the level of adoption of AI within companies that could make them more sustainable, and the second should reflect on internal processes, including proper data management practices and interactions with company clients. This paper tries to further research this gap by examining different factors influencing the application of AI and Big Data in companies, such as investments in technology and people, data-to-value maturity level, regulatory compliance, and lastly, partnerships with other players in the AI ecosystem. Therefore, having identified in the introduction what is known and what is not known currently, two research questions were defined as follows:

RQ1: *Which factors are key for determining AI adoption index level in medium and large-sized companies?*

RQ2: *What are the typical profiles of medium and large-sized companies with determined AI adoption index levels?*

The authors tried to determine what is the current state of strategic integration of AI in company business processes. This was performed by analyzing different insightful parameters within empirical research, including a sample of 240 medium and large for-profit companies, all registered in Serbia. This paper is organized in the following manner. In Section 2, a summary of the existing literature is provided for determining key theoretical findings of data-driven decision making in companies. Section 3 displays the methodological framework for applying AI adoption index within the sample of companies from Serbia, and a breakdown of research instruments that were used. Section 4 displays results of the quantitative research by offering descriptive statistics, analysis of regression results, and company profiling using clustering (K Means algorithm). Section 5 includes a presentation of the main findings, comparison with other similar research, and discussion of other previous relevant papers. The paper concludes in Section 6 with an announcement of future research plans regarding this topic.

The main contribution of this research lies in the examination of AI's role in sustainability efforts of medium and large-sized companies in Europe and the West Balkans specifically. The paper delves into how the strategic integration of artificial intelligence (AI) concepts plays a pivotal role in enhancing sustainability efforts within for-profit businesses. It provides implications of AI integration in two key areas: data management within organizations and the diversification of human engagement in digital ecosystems. The results of the analysis and interpretation of AI adoption index in medium and large companies provide the identification of three separate groups of companies with low, moderate, and high AI adoption index. These groups were profiled with several important dimensions, enabling proper understanding of why different factors are important and how are they influencing AI adoption in companies.

2. Theoretical Review

Having in mind that data-driven decision making is a fundamental strategy for many companies, this fact is underpinned by theoretical frameworks that may guide the integration of AI and Big Data into everyday operations. This chapter explores key theoretical perspectives that form the foundation of the strategic integration of artificial intelligence in terms of sustainability. The authors carried out a theoretical review to identify the most important factors that influence AI adoption level in for-profit companies. The literature review is organized in three sections: competitive landscape, data management practices, and AI and Big Data utilization in end user interactions. This chapter concludes with the formulation of a research hypothesis which will attempt to provide answers to the main research questions.

2.1. Competitive Landscape for AI Integration

Big Data represents a distinctive and valuable resource. Companies that organize and manage their data according to industry standard, when harnessed effectively through AI technologies, can gain a competitive edge in the market [13]. This subchapter explores key factors defining the competitive landscape for AI integration, by analyzing market trends, the period of AI adoption, technology readiness, investments in AI infrastructure, and AI talent management and collaborations.

Findings from PwC [14] and Adobe [15] currently suggest several important market trends:

- Most executives say AI tools in companies have boosted productivity already, supported cost savings, and enabled innovation of products and services for the needs of the market.
- The pressure of competition is significant, since falling behind in AI adoption is one of the major concerns among customer experience leaders and mainstream companies in different industries.
- There is an increasing trend of large companies investing in AI, when compared to the period of the last 5 years, so there is evident disruption in today's businesses, leading to AI becoming the mainstream technology.
- US-based companies, as the forerunners, mostly agree that adopting AI technology has helped them create better customer experiences.

Schneider [16] concludes that data generated through various business processes in companies holds immense value for decision making, customer insights, and operational optimization, while Wang [17] and Nishant [18] discovered additional opportunities for exploitation in everyday business practice. Nowadays, access to high-quality data and the capability to utilize AI effectively is not a common thing in the competitive landscape, giving such companies that manage data well a rare advantage.

While the old world of making decisions based on intuition and experience is going away, the new world is faced with the paradigm of inimitability. This signifies a strategic decision by the company to copy the best experiences of other companies, or the decision to build from scratch the infrastructure, expertise, data studied in [19], and algorithms required for AI and Big Data integration.

When observing the competitive landscape for integrating AI, we must include differing views and approaches. One of the primary aspects is the difference between early adopters of AI and Big Data and late adopters, as studied in [20]. Toniolo [21] analyzed the timeline for the adoption AI and Big Data concepts over the period of the last 10 years. In the case of early AI adopters, key findings suggest that a smaller portion of European companies have embraced AI as a strategic imperative, gaining a competitive edge through data-driven decision making. Such companies leveraged AI to optimize operations, enhance customer experiences, and develop innovative products or services. This has been confirmed by Hansen [22] in his exploration of concepts for versatile AI application in industrial SMEs.

Findings also stress that companies that found the "right formula" for AI adoption 10 years ago are now the frontrunners in their industries. On the other hand, a larger portion of companies in real-world business are cautious about AI adoption, often due to concerns about costs, technical complexities, or data privacy. These late adopters risk falling behind in terms of efficiency, agility, and competitiveness, and for the last 3 years, after the major pandemic, the consequences of late adoption of AI and Big data concepts are more and more visible.

On the other hand, when it comes to the technological maturity of the company, the primary stage of becoming AI-ready is to increase the share of digital (populating large quantities of Big Data) versus traditional (outdated) data, where most records are in paper or other non-digital format [23,24]. Regarding the technological readiness to convert raw data to measured value for the company, tech-savvy companies with advanced IT infrastructure are better positioned to integrate AI seamlessly. They can leverage their existing capabilities to implement AI solutions effectively. Companies with outdated technology infrastructure may face challenges in the adoption process, since they need to invest in upgrading their systems, which can be resource-intensive and time-consuming [25].

AI technological investments as a factor involve two capacities: Capex (which can be used for managing Big Data platforms, integrations and upgrades, innovation projects in data science and machine learning) or operating costs (issued for licenses for AI and Big Data tools in the company, or finally, AI-related education for company employees) [26]. Lee [27] investigated AI investment amounts and concluded that the benefits of AI adoption are greater at firms that also invest in complementary technologies and pursue internal R&D strategy. This is in line with research by Kelly [28], who examined 60 studies on what factors contribute to the acceptance of artificial intelligence.

Additionally, it is also important to choose between in-house talent skilled with AI and the engagement of third-party experts [29]. Existing research focuses heavily on human resource potential for this area of science, and results demonstrate that companies with in-house AI expertise invest in nurturing in-house AI expertise, obtaining a competitive advantage that way [30,31]. They can quickly explore and discover new data, mingle data with existing resources, and finally, tailor AI solutions to their specific needs in business.

Finally, when it comes to analyzing frequent collaborations with AI ecosystem, we can distinguish between two options: collaborative (doing business with AI startups, academia, institutes) and AI competitive (keeping AI strategy secret) [32,33].

On the other hand, reliance on third-party providers is relevant in the case of companies open to outsourcing AI capabilities, to minimize time needed for exploration and pilots, enabling specialized vendors or service providers to provide quick results that way. Those solutions can be customized up to some point, but it is necessary to control and align all third-party providers. Regarding partnerships of companies with other, more specialized partner companies for AI, it is noticeable that larger companies tend to collaborate with AI startups, research institutions, or industry peers to collectively advance AI capabilities. Such partnerships can accelerate innovation and foster industry leadership, and mainly it has not been perceived as a factor of competitiveness in the previous period. The smallest portion of companies (mostly Big Tech companies) have opted to create their own platforms, services, and other means for AI implementation [34,35].

From analyzing existing research material on the competitive landscape of AI integration, it can be concluded that regarding the AI adoption index in medium and large-sized companies, there are several factors that should be further examined: the number of years applying Big Data and AI, annual investments in AI infrastructure, share of employees trained in Big Data and AI, and number of collaborations within the AI ecosystem (other companies in the country or region).

2.2. Data Management Practices around Use of AI

Effective data management is the linchpin of the strategic integration of AI into the daily decisions of medium and large-sized companies. This subchapter explores data management practices connected to using AI in improving both internal and external processes, by analyzing data governance frameworks, regulations about data privacy, and protection of personal record data.

Robust data governance (analyzed in detail by Boddington in [36]) is essential for managing the increasing volumes of data generated daily by European companies. These organizations recognize the importance of well-defined data governance frameworks, which encompass processes, policies, standards, and metrics that ensure data quality, security, and compliance with regulatory requirements. Bessen [37] analyzed the context of AI and Big Data, where data governance framework serves to ensure the following key purposes:

- data ethics;
- data security;
- regulatory compliance.

Regarding data ethics, Rhem [38] analyzed theoretical models in data ethics guiding European companies in responsible data management, by encompassing ethical considerations about collecting only the data necessary for the intended purpose.

When it comes to data security and ensuring informed consent of people's data processed by AI, according to Mandy [39] and Brasseur [40], it is mandatory to ensure that individuals are informed about how their data will be used and obtain their explicit consent. Also, studies outline transparency and accountability within data access and control to integrally ensure that AI algorithms and data-driven decisions are fair and unbiased [41].

Also, regarding regulatory compliance, Timan [42] investigated European companies, and found that they not only comply with general data protection regulations, but also recognize that ethical data practices are essential for building and maintaining trust with their clients. In the case of Serbia, as a candidate member country for the EU, GDPR is still not obligatory but existing legislation is currently being adjusted for the process.

From analyzing existing research material regarding data management practices, it can be concluded that for the AI adoption index in medium and large-sized companies, there is one key factor that should be further examined—the connection between the data governance framework and the use of AI.

2.3. AI Utilization in Interactions with Clients

The integration of AI and Big Data into everyday company decisions extends to client omnichannel interactions, where these technologies offer tremendous potential for personalization and predictive analytics. This subchapter explores the practical applications of AI and Big Data in improving both internal and external processes, by analyzing important factors such as the scope of internal business processes that include Big Data and AI, as well as the level of AI applications in actions towards external clients.

By leveraging AI and Big Data for predictive analytics, for-profit companies cannot only meet but also anticipate their clients' expectations. Such a proactive approach has been analyzed by Rutter [43] and Burnaev [44], and the results of the study showed improved client interactions. One of the primary benefits of AI and Big Data integration in interactions with clients is the ability to offer highly personalized products and services to clients, which has been very much studied by various researchers from the aspect of business effectiveness and business efficiency or precision [45,46]. From analyzed studies, it can be concluded that AI adoption is directly influenced by the number of business processes that are improved or rebuilt with the help of AI.

Takyar [47] analyzed the use of AI in seven major for-profit industries, determining NLP and computer vision models as the models with the broadest application potential. In existing research [48–50] analyzing the level of AI applications in interactions with clients, studies suggest that certain companies target specific niches or industries where

AI adoption is less common, and such companies establish dominance by leveraging AI early. Other companies may aim for broader market adoption and mass appeal. They use AI to create products or services with wide-ranging applications, intending to capture a larger market share. Banners and Hunnermund [51] find in their study of 6000 German companies that AI adoption is on a more mature level if the level of AI being applied in everyday interactions is more intense, and often joint ventures serve as a good disruption point.

From analyzing existing research material regarding the utilization of AI, it can be concluded that for AI adoption index in medium and large-sized companies, two factors are worth further examination—scope (number) of business processes including AI, and level of AI being applied in B2C/B2B interactions.

2.4. Research Hypothesis Formulation

From defined research question and through a literature review, the authors identified two research hypotheses that should be analyzed further via quantitative research.

H1. *The key factors positively influencing the adoption of AI in medium and large-sized companies are the number of AI applications, investments in AI infrastructure, and share of employees trained for the use of AI.*

H2. *Low, medium, and high levels of AI adoption index are three separate groups of company profiles that can be identified and analyzed separately.*

Now follows a chapter defining the methodological framework for conducting quantitative research.

3. Methodological Framework

3.1. Sample Description

The sample of 178 medium and 62 large-sized for-profit companies includes businesses with an employee structure greater than 50 and less than 250 (medium-sized companies) and above 250 employees (large companies), with revenue above EUR 5 million annually. All sampled companies are doing business in Serbia. The sampled companies come from various industries, covering IT, agriculture, banking, telecommunications, logistics, manufacturing, and ecommerce. Descriptive statistics for all sampled companies are presented in Table 1.

Table 1. Profile of sampled companies.

		Freq.	% of Total
Company size	Medium	178	74%
	Large	62	26%
Country of origin	Serbia	144	60%
	EU	69	29%
	Rest of world	27	1%
No. of years doing business	1–5	14	6%
	6–15	97	40%
	16–25	109	45%
	26+	20	9%

Table 1. *Cont.*

		Freq.	% of Total
Industry	IT	45	19%
	Banking	7	3%
	Agriculture	14	3%
	Telecom	14	6%
	Logistics	35	15%
	Manufacturing	68	28%
	Ecommerce	57	24%
Annual revenue range	EUR 5–10 million	44	18%
	EUR 10–50 million	102	43%
	EUR 50–100 million	76	32%
	EUR 100 million+	18	8%

These companies deal with different types of digital transactions and records, structured data, but also with a lot of unstructured data such as images, audio, and video files.

A precondition for the selection of companies for this research was the existence of a business intelligence unit or data warehouse unit in the company, which implies the existence of data in various forms [52,53]. Of course, if the company in question had intelligent automation of business processes or data science research teams, that would be considered as a surplus. Data officers were suggested to review the data governance framework as a factor of AI adoption, but all of them outlined that data governance principles are not yet in use within their companies.

3.2. AI Adoption Index Framework

To empirically analyze the AI adoption index, which quantifies the extent of AI adoption within a company, the authors applied guidelines from Stanford's AI Index report [54] for 2023. This framework involves means to analyze companies regarding processes of data collection, analysis, and interpretation of results. This framework has been applied on the sampled 240 medium and large-sized companies from Serbia.

In order to appropriately comprehend the scale of the conducted research, the authors defined Figure 1, with key points outlined graphically.

In general, after the literature review and conducting the survey, key factors can be identified that can be used for scoring AI adoption index. After that, K Means clustering was performed to be able to interpret research results, and finally, correlations and descriptive statistics were obtained to complete profiles of all surveyed companies.

The main point of contact from each company was the data officer, who supported the whole process of gathering components necessary for determining the AI adoption index. Correspondence was carried out electronically, and one of the authors of this research was defined as the facilitator of the data collection process. Below is displayed the process of conducting research within th sampled companies, as well as the process of determining the AI adoption index for 2023.

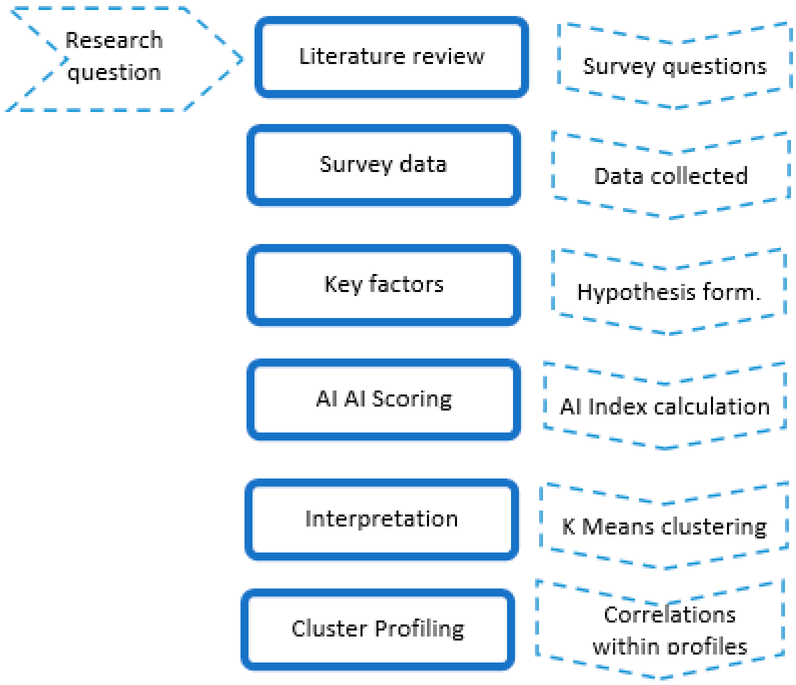

Figure 1. Study model.

Instrument Design—AI Adoption Index Components

The initial step was to clearly define the components that make up the AI adoption index. In the case of this specific research, these components include the following:

- Number of AI applications: Count the distinct AI applications or use cases implemented within the company. Of course, a necessary precondition is that the observed company "lies" on a lot of structured and unstructured data.
- Investment in AI Infrastructure: Quantify the financial resources allocated to AI-related hardware, software, and infrastructure. This can include continuous improvements in the form of capital expense, but also existing licensing and maintenance costs.
- Share of employees trained in AI: Determine the percentage of employees who have received AI-related training or certifications. A precondition for this factor is an established data literacy concept in the company, with a skilled workforce able to work in data science and machine learning operations.

The authors collected relevant data for each of the defined components. It was mandatory to keep track of data validation and quality, so the authors ensured that the data were normalized before going into further procedures. After joining all data into one, integral dataset, standardization and scaling was performed.

Each component listed above had to be broken down into research factors and assigned with appropriate weights (0.1 was the minimum weight), based on their relative importance in measuring AI adoption. Data officers from sampled companies defined weights for each factor; the results after normalization are displayed in Table 2 below.

Table 2. Weights assigned for each factor.

Research Factor	Assigned Weight
Number of years applying Big Data and AI	0.1
Share of business processes that include Big Data and/or AI	0.1
Total number of AI applications	0.2
Annual investments in AI infrastructure	0.2

Table 2. *Cont.*

Research Factor	Assigned Weight
Share of employees trained in Big Data and AI	0.2
Number of collaborations with AI ecosystem	0.1
Share of partnerships in total implementation of AI innovation projects	0.1

For the calculation of AI adoption index, a standard formula was used, as follows:

AI Adoption Index = (Weight1 $\times$ Component1) + (Weight2 $\times$ Component2) + (Weight3 $\times$ Component3).

The minimum value for AI adoption index is 0, and that value corresponds to companies that are rated 0 for all components. On the other hand, the maximum value for that index is 1, signifying all companies that have reached their full potential for all components.

4. Results of Quantitative Research

This chapter includes a presentation of the main research results. One of the first steps after scoring AI adoption index is to compare the calculated AI adoption index within and between inputs such as industry sector. This provides context for understanding the company's AI adoption relative to others in the same group. Table 3 displays the share of companies measured with low, medium, and high correlations between the AI adoption index as the output value and industry sector as the input parameter.

Table 3. Measured correlation for AI adoption index across industry sectors.

		Versus Overall Average	Within the Same Industry Sector			Between One and All Other Industry Sectors		
			Low Correlation *	Medium Correlation *	High Correlation *	Low Correlation	Medium Correlation	High Correlation
Industry	IT	+21%	4%	12%	84%	47%	20%	23%
	Banking	−5%	32%	22%	46%	7%	17%	76%
	Agriculture	−14%	35%	41%	24%	76%	11%	13%
	Telecom	+11%	21%	13%	66%	38%	22%	40%
	Logistics	+3%	15%	19%	68%	42%	23%	35%
	Manufacturing	+11%	14%	10%	76%	49%	37%	14%
	Ecommerce	+26%	5%	10%	85%	55%	32%	13%

* Low correlation equals values below 0.3, medium corr. equals values between 0.3 and 0.7, high correlation equals values above 0.7.

From Table 3, it can be learned that the highest correlation for AI adoption index values was recorded within Ecommerce, IT, and Manufacturing industries, while the most significant differences exist within Banking and Agriculture industries, meaning that probably there are an equal share of companies with low AI adoption index compared to the share of companies with a high level of AI adoption index.

Below is Table 4, displaying descriptive statistics after determining AI adoption index score.

Table 4. Descriptive statistics of AI adoption index scores.

AI Adoption Index (0—Minimum Value; 1—Maximum Value)	Mean Value	Median Value	Standard Deviation	Minimum Value	Maximum Value
Medium-sized companies	0.32	0.24	0.34	0.03	0.72
Large-sized companies	0.23	0.26	0.12	0.04	0.83

Having in mind Table 4, it can be concluded that medium-sized companies record slightly higher levels of AI adoption index on average, but when observing and analyzing where the majority of sampled companies are positioned, it can be concluded that large-sized companies have slightly higher AI adoption index (the median value is higher in the case of large companies from the sample). More detailed explanations on Figure 2 shall be given.

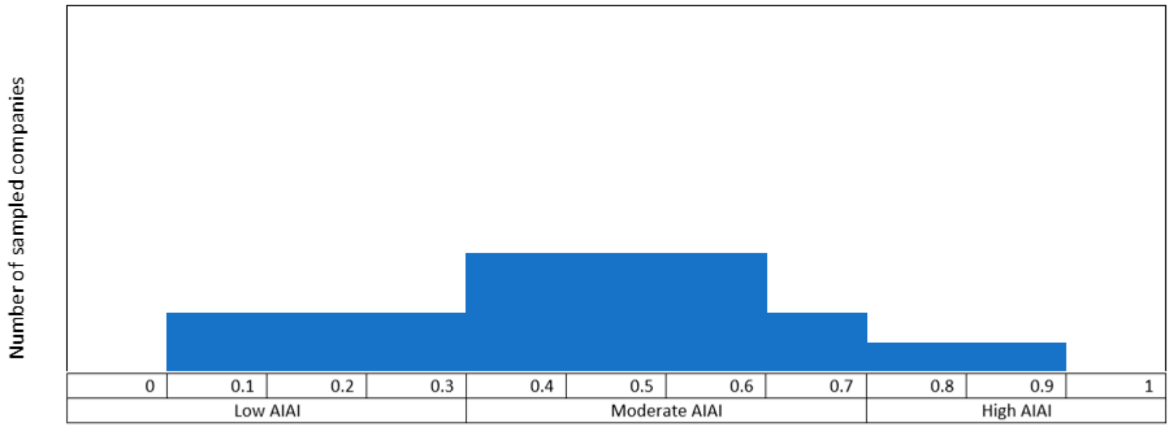

Figure 2. Distribution of AI adoption index (AIAI) across sampled companies.

Below is Table 5, displaying the categorization of companies by adoption index. It is possible to identify companies with low AI adoption index, and those companies are experimenting with AI. Companies with a medium level of AI adoption index are rebuilding and innovating their business processes with AI, and AI achievers are those companies with a high level of AI adoption.

Table 5. Categorization of companies by AI adoption index.

AI Adoption Index	Number of Sampled Companies
Low (less than 0.3)	65 (27%)
Medium (between 0.31 and 0.70)	163 (68%)
High (higher than 0.71)	12 (5%)

It is essential to analyze key factors influencing AI adoption index. The results of linear regression can be seen in Table 6, displaying regression coefficients and standard error values, along with the *p*-value, indicating the overall statistical significance of the results.

It can be concluded that four factors influence AI adoption index significantly. Those factors are number of years applying Big Data and AI, share of business processes that include Big Data and/or AI, total number of AI applications, and annual investments in AI infrastructure. On the other hand, company size and number of collaborations with the AI ecosystem do not represent important factors for the definition of AI adoption index.

Also, it can be concluded from everything above that the first hypothesis is confirmed.

Below in Table 7 are presented the results of comparing AI adoption index levels between medium and large companies from the sample.

It can be seen from Table 7 that in the case of medium-sized companies, AI adoption index level is mostly moderate and low, which can be an input for further analysis. On the other hand, the majority of companies with a high level of AI adoption are large companies (90% of those companies started applying Big Data and AI concepts 10 or more years ago).

Regarding key insights about the three groups of companies with distinct AI adoption index (low, moderate, high), profiling of these groups has been carried out with the use of K means algorithm (k equals 3, silhouette score is above 0.5, Rand index and ARI are within expected values), and the results are displayed in Table 8. It can be easily seen and analyzed from Table 8 that companies with low AI adoption index are somewhat new to the AI concept, have only one or two automated business processes out of one hundred, and invest small portions of money in only a few applications of AI.

Table 6. Factors influencing AI adoption index.

Means for Obtaining Data about Factor	Variable	Coefficient of Regression	Standard Error	*p*-Value
Publicly available database	Company size	0.13	0.12	0.04
	Annual revenue	0.23	0.14	0.01
	Industry type	0.22	0.03	0.01
Data delivered by data officer from sampled company	Number of years applying Big Data and AI	0.45	0.31	0.01
	Share of business processes that include Big Data and/or AI	0.49	0.12	0.01
	Total number of AI applications	0.67	0.11	0.01
	Annual investments in AI infrastructure	0.59	0.05	0.01
	Share of employees trained in Big Data and AI	0.38	0.45	0.03
	Number of collaborations with AI ecosystem	0.19	0.11	0.01
	Share of partnerships in total implementation of AI innovation projects	0.35	0.21	0.01

Table 7. Comparison of AI adoption levels (medium vs. large companies).

AI Adoption Index	Medium Companies	Large Companies	Total
Low	57	18	65
Medium	118	35	163
High	3	9	12
Total	178	62	240

The moderate profile consists of a much broader range of values for key factors; therefore, the share of business processes that are automated reaches 14%, and overall annual investments in AI reach EUR 20 million (20 times higher than in the case of low-AI-adoption companies). Lastly, companies profiled with high AI adoption index are all early adopters of AI (applying it for at least 10 years), have up to almost 20% of their business processes automated, and invest a minimum of EUR 20 million annually in AI infrastructure (use cases, tech, etc.). From all of this, it can be concluded that companies can be diversified according to the determined AI adoption index, and here lies a clear opportunity to build prediction models of AI adoption index, based on input factors' data.

After all analyses performed, it can be concluded that the second hypothesis can be confirmed, with the statistical significance confirmed after employing the K Means algorithm.

Table 8. Profiling of three groups determined by AI adoption index.

	AI Adoption Index		
Key Factors	**Low**	**Medium**	**High**
Number of years applying Big Data and AI	Less than 6 years	6–9 years	9+ years
Number of years in business	More than 16 years	Between 6 and 25 years	Less than 10 years or more than 25 years
Share of business processes that include Big Data and/or AI	2–4%	5–14%	15–19.5%
Total number of AI applications	Less than 10	Between 11 and 15	More than 15
Annual investments in AI infrastructure	Less than EUR 1 million	Between EUR 1 and 20 million	Above EUR 20 million
Annual revenue range	Less than EUR 10 million	Between EUR 10 and 100 million	More than EUR 100 million

5. Key Findings and Discussion

The conducted research on the strategic integration of AI and Big Data in everyday company operations, particularly within the analyzed sample of 240 medium and large-sized companies from Serbia, provides new and valuable insights into the state of AI adoption in the Balkans, Europe. Both research hypotheses were confirmed; therefore, it can be stated that main research questions have been answered.

However, this discussion reflects on the application of AI adoption index and the implications of the research findings for existing studies. A comparison of research results between this study and other, similar papers is displayed in Table 9.

Table 9. Comparison of research results with previous research on AI adoption index.

Factors	Results of This Research	Bettoni [55]	Rhawashdeh [56]	Chatterjee [57]
Number of analyzed factors	7	5	5	9
Number of companies in sample	240	39	236	340
Average AI adoption level	Medium	Medium	High	Medium
Profiling of sampled companies performed	Yes	No	No	Yes

From the table above, it can be determined that the conducted quantitative research within this paper involves more than the average number of factors in AI adoption index analysis, with a solid sample size (having in mind that this analysis covers medium and large-sized companies, which are harder to find and reach).

Regarding the average AI adoption level from all four analyzed research results, it can be derived that sampled companies were rightfully selected for research purposes. On top of this, this research offers profiling of companies based on AI adoption level factor similarity, which has only been seen in the highly referenced study from Chatterjee [57].

The novelty of this research lies in its unique contributions in the realm of AI applications in business sustainability:

- Theoretical findings determined several components of AI adoption index that are key for surveying data officers from sampled companies.
- Results of quantitative research uncovered distinct AI adoption profiles among medium and large companies.

Now follows a subchapter covering the most important, distinctive insights that provide a valuable foundation for future research on data-driven approaches in companies.

5.1. Key Findings and Insights

This research showed variations in the level of AI strategic planning among the sampled companies. The findings are that some companies may have well-defined AI strategies, while others may still be in the early stages of AI adoption. Since understanding these differences is crucial for identifying future challenges and opportunities, it was important to cross-check findings with previous papers. Therefore, it can be concluded that the findings from this paper are in line with [58,59], where it was previously discovered that companies with well-established AI strategies are likely to have a competitive advantage in terms of efficient AI integration.

In the theoretical part of the research, it was concluded that effective data management is fundamental to AI integration. On the other side, within the quantitative research part of this study, it was not possible to uncover disparities in data quality, governance, and privacy practices among the sampled companies, since data officers reported that there are no data governance frameworks implemented. In existing studies, McKinsey [60] states that companies with strong data management practices are better positioned to leverage AI's full potential. Those with gaps in data management need to prioritize improvements to unlock the value of their data assets. Since this has been examined only in theoretical boundaries, it can be concluded that here lies a clear potential for future improvement on this research.

From this research, it was found that the readiness of the technology infrastructure for AI integration is a critical factor for adopting AI in a company. The research results are in line with existing research, since there are findings of correlations within companies that have already invested in AI-ready systems and recorded improvements in company performance, while others may need significant upgrades [61]. Additionally, Thayyib [62] showed that companies with advanced technology infrastructure can expedite AI adoption. Others may need to allocate resources to modernize their IT environments to support AI initiatives effectively.

This research might have revealed variations in the level of AI awareness and acceptance within company employee culture, finding that investing in AI talent and skills positively influences AI adoption. Employee buy-in and readiness for AI-driven changes are vital, as was confirmed in [63]. Consequently, companies with a culture of curiosity and adaptability to change that fosters AI innovation are more likely to succeed in AI integration [64].

While research findings indicate how AI adoption impacts competitiveness within the Serbian business landscape, it can be stated that companies that embraced AI 10 years ago may have experienced improved market positioning and operational efficiency. These findings have been checked for in the existing literature, about businesses that lag in AI adoption. The results are in line with this, because other studies examined companies facing challenges in keeping up with competitors who have already embraced AI and achieved improved outputs [65–67].

Lastly, from the perspective of understanding how regulatory factors influence AI adoption, it must be noted that compliance with data privacy regulations, such as GDPR, is essential, which was explored within this paper and confirmed in [68]. However, businesses operating in Serbia and the broader Balkan region should stay informed about evolving regulatory requirements related to AI and Big Data, since there will come the day that Serbia enters the European Union.

Future Directions: The research should also provide insights into the future directions of AI adoption in the region. It might highlight emerging AI trends and areas where companies plan to invest further. Implications: Companies should align their AI strategies with future trends to remain competitive and resilient. Anticipating shifts in AI technology and applications is essential for long-term success [68–72].

The limitations of this research lie mostly in the low availability of companies in Serbia for conducting field research involving data and the use of AI in everyday business. Additionally, a very important limitation is the fact that a significant share of medium and large-sized companies in Serbia do not manage their data at all, meaning that the AI adoption index in most Serbian companies is still far away from optimal values.

A specific limitation of this research is the fact that none of the analyzed companies implemented a data governance framework, so it was impossible to analyze that factor within the quantitative research.

5.2. Potential Implications

According to previously made findings and theoretical conclusions, these are the key implications of a company's attempts to integrate AI into everyday business practice:

- Innovation: Theoretical integration of AI into sustainable business practices can drive innovation. AI-powered technologies can create new sustainable products, services, and business models [73].
- Operational Efficiency: AI can optimize resource use, reduce energy consumption, and enhance supply chain efficiency, leading to cost savings and improved profitability [74–76].
- Environmental Impact: Theoretical frameworks help businesses evaluate and minimize their environmental footprint. AI facilitates real-time monitoring and data-driven decisions to reduce waste and emissions [77].
- Impact on Green marketing: On the one hand, AI applications and systems in marketing—in essence—pursue sales' objectives and increase consumption, but on the other hand, AI in marketing can be a powerful force in promoting supply- and demand-side sustainability efforts [78].
- Human Capital Development: Integrating AI into sustainability practices necessitates training and upskilling the workforce. This investment in human capital can lead to a more skilled and adaptable workforce [79,80].

The strategic integration of artificial intelligence for sustainable businesses, with specific attention to medium and large-sized companies, presents a multifaceted endeavor. It necessitates effective data management practices, a commitment to ethical AI deployment, and a focus on enhancing human user engagement. In the digital era, businesses that harness the power of AI for sustainability not only secure their future but also contribute positively to the environment and society, paving the way for a more responsible and prosperous world [81–84].

6. Conclusions

In the context of the West Balkans, and specifically Serbia, the strategic integration of artificial intelligence (AI) into sustainability efforts among medium-sized and large companies offers a promising avenue for addressing pressing regional challenges while harnessing the potential for sustainable growth. This convergence of AI and sustainability represents a pivotal step towards economic development, environmental stewardship, and social progress towards the European Union [85–87].

Serbia, like many West Balkan countries, faces a unique set of sustainability challenges, including environmental degradation, resource scarcity, and the need for economic diversification. The adoption of AI technologies can empower companies to address these issues more effectively. For instance, AI-driven solutions can play a critical role in optimizing energy consumption, managing water resources, and enhancing agricultural practices, aligning with broader sustainability objectives in the region [88–90].

Moreover, the strategic integration of AI offers opportunities for enhancing regional competitiveness. Companies that leverage AI for supply chain optimization, product innovation, and data-driven decision making can improve their market positioning, both locally and globally. This, in turn, can attract foreign investments and foster economic resilience, crucial for the region's ongoing development [91–93].

Sustainability reporting and transparency are also vital considerations for companies operating in Serbia and the West Balkans. AI-powered data analytics can facilitate more accurate and comprehensive sustainability reporting, enhancing accountability and aligning with the global trend towards increased ESG (Environmental, Social, and Governance) disclosure. This, in turn, can contribute to attracting responsible investments and reinforcing the region's commitment to sustainable practices.

However, it is essential to recognize that the successful integration of AI into sustainability efforts in the West Balkans, including Serbia, hinges on several key factors. These include the development of robust digital infrastructure, fostering a culture of innovation and collaboration, and addressing ethical and regulatory challenges associated with AI.

Future research plans on this broad topic include the following:

- AI Adoption and Regional Dynamics: Investigate the factors influencing the adoption of AI for sustainability in the West Balkans, with a special focus on the blooming IT sector in Serbia. Analyze how political, economic, and cultural factors shape the strategic integration of AI in different sectors and regions within the West Balkans.
- Ethical and Regulatory Frameworks: Examine the ethical implications of AI integration and propose guidelines and regulatory frameworks tailored to the West Balkans. Explore the balance between innovation and ethical considerations to ensure responsible AI-driven sustainability practices.
- AI-Driven Impact Assessment: Develop methodologies to assess the tangible environmental, social, and economic impact of AI integration in West Balkan companies. Quantify the benefits and challenges to provide empirical evidence for informed decision making and policy development.

In conclusion, the strategic integration of AI into sustainability efforts among medium-sized and large companies in the West Balkans, with a specific focus on Serbian for-profit companies, holds immense potential for catalyzing sustainable development, contribution to economic growth, and environmental protection in the region. By embracing AI-driven solutions and fostering a conducive ecosystem for innovation, these companies contribute to a more sustainable and prosperous future while addressing the unique challenges faced in the West Balkans. This journey toward sustainability through AI integration underscores the region's commitment to global sustainability goals while seizing the opportunities of the digital age.

Author Contributions: Conceptualization, D.M.C.; methodology, S.D.J.; software, D.M.C.; validation, D.M.C. and S.D.J.; formal analysis, S.D.J.; investigation, S.D.J.; resources, D.M.C.; data curation, D.M.C.; writing—original draft preparation, S.D.J.; writing—review and editing, S.D.J.; visualization, D.M.C.; supervision, S.D.J.; project administration, D.M.C.; funding acquisition, S.D.J. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Not applicable.

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

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