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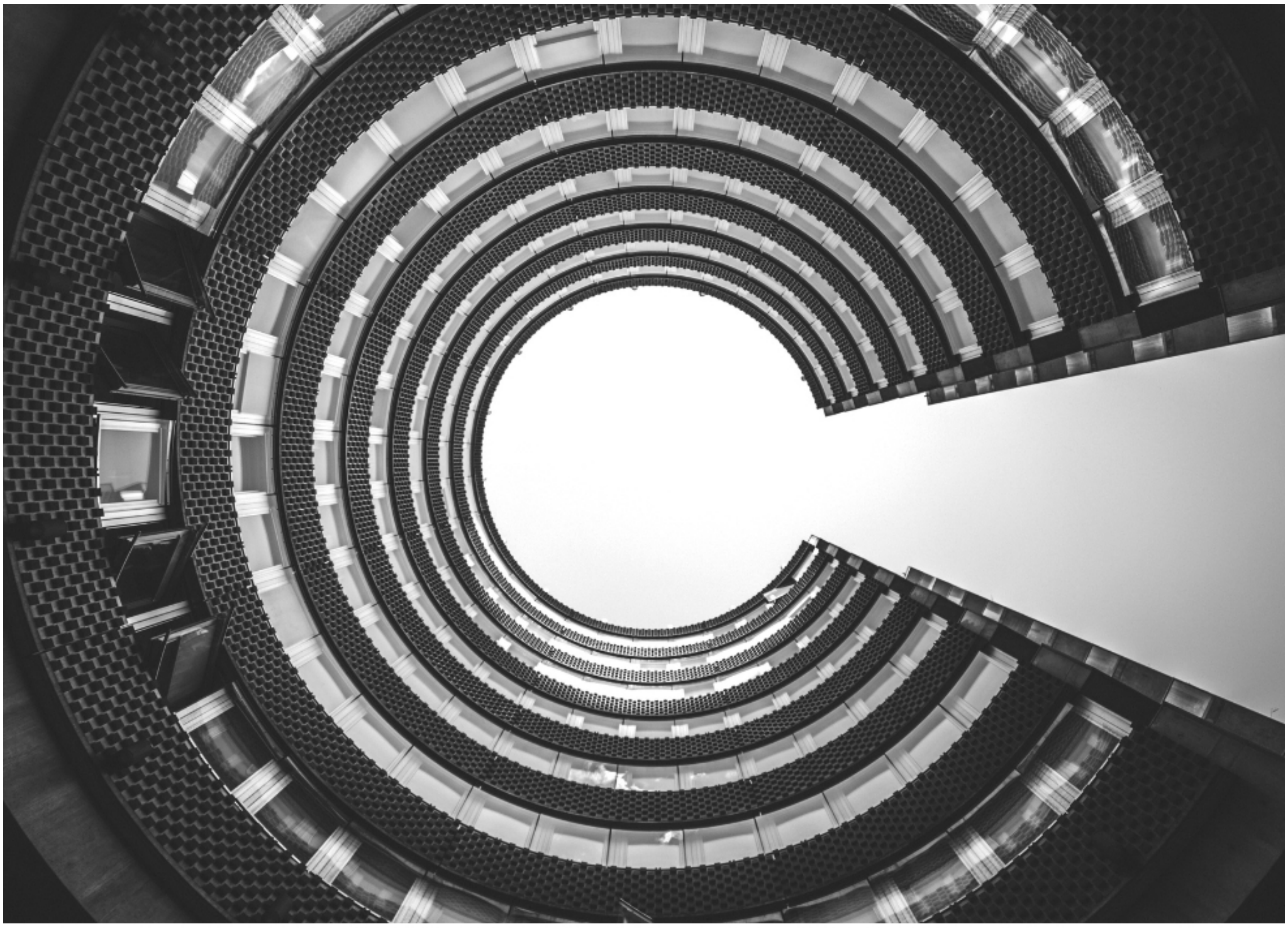

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WELCOME MESSAGE

PROF. DR. ISMAIL KOCAYUSUFOĞLU
Editor-in-Chief, *CIT Review Journal*
Rector, Canadian Institute of Technology

Dear Readers, Colleagues, and Friends,

It is a true pleasure to welcome you to the May 2025 edition of the CIT Review Journal. As both the Editor-in-Chief of CRJ and the Rector of the Canadian Institute of Technology, I am proud to introduce this issue, which brings together thoughtful research and fresh perspectives on some of the most pressing and exciting topics of our time.

This edition delves into significant themes that are influencing our future landscape. These themes encompass transformative trends, evolving technologies, and critical issues that impact our daily lives, organizations, and communities. They represent both challenges and opportunities that demand our attention and action as we navigate an increasingly interconnected world.

At CIT, we strongly believe in fostering dialogue, sharing knowledge, and building bridges between disciplines and communities. The articles featured in this issue reflect those values—offering not only academic insight, but also practical implications and forward-looking solutions.

I want to sincerely thank all the authors, peer reviewers, and editorial contributors who have given their time, energy, and expertise to this issue. Your work helps us create a space where ideas can grow and lead to new ways of working together and doing research.

To our readers, thank you for your continued interest and support. Whether you are an academic, a student, or simply a curious mind, we hope this edition inspires new ideas, challenges your perspectives, and encourages further exploration.

With warm regards,

Prof. Dr. Ismail Kocayusufoğlu
Editor-in-Chief, *CIT Review Journal*
Rector, Canadian Institute of Technology

GREETINGS REMARKS

MARTIN NECPAL
Faculty of Material Science and Technology in Trnava
Slovak University of Technology in Bratislava

Greetings to all readers of this edition of the CIT Review Journal (CRJ). This publication delves into crucial topics that are increasingly significant in our fast-paced technological and industrial landscape. The focus areas of this issue—including Digital Transformation, Artificial Intelligence in Management, the Digital Divide, Data-Driven Roadmaps in Agriculture and Economy, a Sustainable and Connected Future, and General Data Protection—address the vital challenges and opportunities that contemporary industries and societies encounter.

As a university lecturer engaged in practical applications within the manufacturing sector, and with a strong focus on the implementation of computer technologies, modeling, and simulation methods, I fully recognize the importance of integrating digital innovations across various fields. The topics covered in this journal not only resonate with current trends but also pave the way toward a smarter, more connected, and sustainable future.

I would like to extend my sincere thanks to the editorial team and reviewers for their dedicated work in maintaining the quality and relevance of the journal. Their professional approach and careful review process ensure that each contribution meets high academic and practical standards.

Finally, I hope that all readers of this edition will find its content both motivating and enriching. I trust that the CIT Review Journal will serve not only as a source of knowledge but also as a catalyst for the formation of new research teams and collaborative projects, encouraging joint efforts in tackling common global challenges.

I wish you an inspiring reading experience and productive reflections.

A CORE FRAMEWORK FOR A BIG DATA MATURITY MODEL IN THE TELECOMMUNICATIONS INDUSTRY

Fatmir Desku [1], ***Adrian Besimi*** [2]

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Abstract

Purpose: This paper is focused on identifying the essential dimensions and sub-dimensions of the Big Data Maturity Model tailored for telecommunication industry by development the core assessment framework. To develop a Big Data Maturity Model tailored for the telecommunications industry by identifying its essential dimensions and sub-dimensions. The proposed model will take into consideration the sector's unique characteristics, including the rapid technological advancements. By providing meaningful information for strategic decision-making, the model seeks to improve the organizational performance of telecommunications companies.

Methodology: This paper uses a qualitative research approach, divided in two phases. The first phase, is focused on desk research to review existing generic Big Data maturity models and identify common dimensions. In the second phase, semi-structured interviews are conducted with ten industry experts and academicians, selected using snowball sampling method, to further define the essential dimensions and sub-dimensions of a Big Data Maturity Model tailored for the telecommunications sector. The data were analyzed using Atlas.ti.

Results: The findings revealed that only the following five dimensions: Data Management, Business Strategy, Organization, Data Governance, and Data Analytics, co-occur across 17 generic big data maturity models six or more times. Analysis of the frequency of codes, code co-occurrence, and the code network revealed that the most frequently mentioned dimensions in expert interviews were Network Performance, Network Modernization, Investments, Market Strategy, Customers, Data Analytics Capabilities, and Organizational Culture.

Conclusions: To create a unified framework, dimensions from the generic models as well as those deriving from the interviews, were integrated in one model that enables the telecommunications industry to assess its Big Data maturity, and includes the following dimensions: Data Governance, Business Development, Data Analytic Capabilities, Network Performance, Network Modernization, Investments, Market Strategy, Customers, and Organization, each containing relevant sub-dimensions.

Keywords: Big Data, Maturity Model,Telecommunication, Performance

INTRODUCTION

This paper is focused on developing a Core Big Data Maturity Model tailored for the needs of the Telecommunication Industry and identifying the key dimensions and sub dimensions of this model. Telecom companies need to assess and enhance their capacities in the use and integration of Big Data in their internal processes, systematically. The paper's proposed model aims to consider the unique characteristics of this sector with the aim of suggesting a framework for strategic decision-making and performance. The telecommunications industry, with its rapid technological advancements, unique business models, and distinctive regulatory environment, has specific needs and complexities that generic models may not adequately address. The final aim of the use of the proposed model is to improve the overall organizational strategical performance of companies operating within this sector.

Given the critical role of Big Data in optimizing operations, improving and facilitating the process of decision-making, maintaining competitiveness, and improving the performance of an organization, a structured approach to assessing and developing Big Data capabilities is essential for the telecommunications sector. Without a dedicated maturity model, companies lack a standardized framework to evaluate their progress and improve their decision making based in data. The development of Big Data maturity ensures improved performance and better adaptation to technological advancements. Therefore, this paper aims to address this issue by developing a tailored Big Data Maturity Model for the telecommunications industry, identifying the key dimensions and sub dimensions necessary for effective assessment and strategic implementation.

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In recent years, the concept of "big data" has become highly significant across different fields, particularly in business and technology. As Wang, Wei, Zhan, and Sun (2017) suggest, the term "big data" refers to "huge datasets," emphasizing the volume and the complexity of the information analyzed. Big Data is considered to play an important role in the telecommunications industry, transforming how operators manage networks, engage with customers, and develop business strategies, especially considering that telecommunication companies have access to a large volume of data (Yongjun, Ming, Shengyong, & Yongbing, 2013). According to Nwanga et al. (2015), the integration of Big Data analytics in telecom is revolutionary, as it allows companies to collect high amounts of data from different sources, such as "call records, internet usage, and customers". By analyzing this data, telecom providers can better understand customer behavior, preferences, and service usage patterns. These data help in optimizing network performance (Jain et al., 2016), personalizing customer experiences, predicting churn, detect fraud (Chen, 2016), and improve the overall business strategies.

Kastouni and Lahcen (2022) discussed the historical chronology of Big Data development in telecommunications in their research paper. According to them, the evolution of mobile networks has shaped data analytics in telecommunications. In the 1G era, data were focused on business operations with limited data inputs from voice and text. With 2G in the early 90s, digital communication introduced new services (SMS, MMS, fax), enabling basic reporting using traditional databases. With the introduction of 3G, data shifted focus to customer behavior analytics. The launch of 4G LTE in 2009 enabled and massive data generation. According to Zahid, Mahmood, Morshed, Sellis (2019) with the rise of smartphones, the 'expansion of social media and IoT, and the emergence of advanced communication networks, the telecom industry is generating and managing a high volume of data on a daily basis'.

Many researchers have been focused on understanding the benefits of the big data in the telecommunication industry. Wang, Wei, Zhan, Sun (2017) have suggested three main applications of big data in the telecommunication sector, including basic business, network construction, and intelligent tracing. Sadiku, Adekunte and Sadiku (2024) have identified the areas the mostly benefit from the use of big data, including here: "Customer Experience, Network Optimization, Operational Analysis, Data Monetization, Fraud Detection, Price Optimization, Customer Churn Prevention, Product Development".

With the aim of understanding whether, an organization is being successfully implementing trends related to big data, many researchers have established Big Data Maturity Models, frameworks designed to evaluate an organization's ability to effectively use big data across different operational dimensions (Langer, 2023). These models assist organizations in understanding their current level of big data and guide them in achieving higher maturity levels by addressing the potential gaps (Wendler 2012). Research by Al-Sai et al. (2022) has identified several big data maturity models, each with unique dimensions and perspectives, suggesting the importance of selecting the model that is most relevant to an organization's specific context.

Awareness of an organization's maturity level in big data is linked to its ability to implement effective strategies that drive performance improvements (Dubey et al., 2019). By assessing their maturity, organizations can 'identify strengths and weaknesses, prioritize investments, and develop strategies that improve their capabilities and competitive positioning' (Ilin et al. 2022). Therefore, understanding the level of maturity is considered as highly important for those that aim to improve their strategic performance based in data.

After a thorough literature review, it was observed that no existing Big Data Maturity Model is tailored to the needs of the telecommunications industry. While Keshavarz et al. (2021) developed a model to assess Big Data analytics capabilities within this sector, it does not align with a traditional maturity model, as it lacks defined maturity levels that allow organizations to assess their position based on their Big Data capabilities. Therefore, the aim of this paper is to develop a foundational framework for a Big Data Maturity Model specifically designed for the telecommunications industry, identifying the key dimensions and subdimensions relevant to its structure.

OBJECTIVE

Given the critical role of Big Data in optimizing operations, improving and facilitating the process of decision-making, maintaining competitiveness, and improving the performance of an organization, a structured approach to assessing and developing Big Data capabilities is essential for the telecommunications sector. Without a dedicated maturity model, companies lack a standardized framework to evaluate their progress and improve their decision making based in data. The development of Big Data maturity ensures improved performance and better adaptation to technological advancements. Therefore, this paper aims to address this issue by developing a tailored Big Data Maturity Model for the telecommunications industry, identifying the key dimensions and sub dimensions necessary for effective assessment and strategic implementation.

RESEARCH QUESTIONS

This section presents the two research questions posed by this paper. The first question focuses on identifying the essential dimensions that should be included in a Big Data Maturity Model for the telecommunications industry, specifically to evaluate an organization's strategic performance. The second question explores the subdimensions that are relevant for assessing the level of a telecommunication organization in terms of Big Data maturity.

Research Question 1: What are the essential dimensions that a Big Data Maturity Model in the telecommunications industry should include?
Research Question 1: What are the essential sub-dimensions that a Big Data Maturity Model in the telecommunications industry should include?

The findings answering these two research questions, will allow the development of the core framework that allows telecommunication companies to assess their level of maturity in the use of big data, in a way that supports their performance.

MATERIALS AND METHODS

To answer the two research questions, this paper uses a qualitative research approach. The data collection process is developed in two different phases. The first phase is focused in desk research, where existing Big Data maturity models are thoroughly reviewed. This review focuses on identifying the dimensions that appear consistently across multiple generic models. The information gained from this step provide a foundational understanding of the common elements of Big Data maturity and inform the development of the interview questions for the subsequent phase. In the second phase, data are collected through semi-structured interviews. The primary goal of this phase is to gather the opinions from industry experts and academicians regarding the essential dimensions and sub-dimensions relevant of the Big Data Maturity Model tailored for the telecommunications sector. Two separate interview guides were developed, one for industry professionals and one for academics, each containing 12 questions.

For the selection of the sample, the following criteria were established: Representation from different countries; Inclusion of professionals from different organizational categories (academia and industry); Expertise in BD applications in key areas such as strategy, operations management, workforce, data utilization, and technology implementation; Extensive professional experience, with minimum of 10 years in roles directly related to academia and industry.

To select experts who fulfilled these criteria, personal contacts were used and with a snowball sampling method. This method was chosen with the aim of identifying suitable participants, ensuring that only those that meet the criteria were included. Interviewees were contacted via email and phone calls. The final sample consisted of 10 interviewees: 5 from the telecommunications academic sector and 5 from the telecommunications industry. The participants were from different countries as follows: Kosovo, Netherlands, Bosnia, Slovenia, Croatia, and Sweden. Eight interviews were conducted via Google Meet; while two interviews were conducted in person. Each interview lasted approximately one hour. The sample size of ten interviewees was considered sufficient, considering the specifics of the industry and the fact that there is a limitation of telecommunication providers that can be targeted and that are willing to response.

Table 1: Participant Details

No.	Interviewer	Location	Role	Years of experience
1	Academia	Kosovo	Professor	12
2	Academia	Netherland	Professor	10
3	Academia	Bosnian	Professor	15
4	Academia	Slovenia	Professor	19
5	Academia	Kosovo	Professor	17
6	Industry	Kosovo	Expert	10
7	Industry	Croatia	Expert	18
8	Industry	Kosovo	Managing Director	11
9	Industry	Sweden	Head of Technical	12
10	Industry	Slovenia	Head of Engineering	14

DATA ANALYSIS

To identify the dimensions that occurred across multiple generic models, a co-occurrence analysis of each dimension was performed. This analysis examined how often specific dimensions appeared across the reviewed generic big data maturity models, helping to identify the most common elements of Big Data maturity. For the interview data, the interviews were transcribed and analyzed using Atlas.ti (a software for analyzing qualitative data). Initially the relevant quotes were coded, and the frequency of codes was analyzed. The meaning of each code was carefully examined to establish links between related concepts and create a network of connections. Additionally, the co-occurrence of codes was assessed to identify relationships and patterns between different dimensions. The frequency and density of codes for each participant were also analyzed, supporting the identification of the most significant dimensions and sub-dimensions as discussed by each expert.structured interviews. The primary goal of this phase is to gather the opinions from industry experts and academicians regarding the essential dimensions and sub-dimensions relevant of the Big Data Maturity Model tailored for the telecommunications sector. Two separate interview guides were developed, one for industry professionals and one for academics, each containing 12 questions.

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RESULTS

This section presents the findings derived from both the analysis of generic Big Data maturity models and the interviews with industry and academic experts.
Findings from the document analysis

The main goal of this section is to analyze the co-occurrence of dimensions in generic Big Data maturity models. The review of the literature identified 17 different frameworks for big data maturity. These include Gartner's Data Maturity Model (Gartner, 2018), IBM's Big Data & Analytics Maturity Model (Nott, 2015), TDWI's Big Data Maturity Model (Halper & Krishnan, 2014), and the Big Data Business Maturity Model Index (Practitioner EMC, 2013, as cited in Al-Sai, 2022). Additional models reviewed were the Maturity Model for Big Data Development (Practitioner TNO, 2013, as cited in Al-Sai, 2022), Maturity Model by Veenstra (Veenstra et al., 2013), Big Data Maturity Assessment Tool InfoTech (Ko & Odetoyinbo, 2013), and the Big Data Maturity Assessment Model Knowledge (as cited in Al-Sai, 2022). The list also includes the Big Data Maturity Framework / El-Darwiche Model (El-Darwiche et al., 2014), Big Data Maturity Model Radcliff (Radcliffe, 2014), A Maturity Model by Betteridge (Netteridge & Nott, 2014), and the Zakat Big Data Maturity Model (Sulaiman & Cob, 2015). Other relevant models are the Big Data Maturity Hortonworks 2016 Model (Dhanuk, 2016), Maturity Model by Adrian (Adrian, Abdullah, Atan, & Jusoh, 2016), A Value-Based Maturity Model (Farah, 2017), the Temporal BDMM Framework (Olszak & Mach-Król, 2018), and the Maturity Model by Comuzzi (Comuzzi & Patel, 2016).
The objective of this part of the research was to identify how frequently the same dimensions appeared across several Big Data maturity models. The findings are presented in Figure 1, showing the dimensions that occur more than twice in different generic models. For the purpose of this paper, only dimensions that appeared more than six times were considered to be integrated in the Big Data Maturity Model, tailored for telecommunication industry. As a result, five key dimensions including: Data Management, Business Strategy, Organization, Data Governance, and Data Analytics, were selected for incorporation into the proposed model.

Figure 1. Dimensions selected for incorporation into the proposed model

Note. The graph includes only those dimensions with a frequency of two or more.

The "Data Management" dimension is present in several Big Data maturity models. These include TDWI's Big Data Maturity Model (Halper & Krishnan, 2014), the Maturity Model for Big Data Development (Practitioner TNO, 2013, as cited in Al-Sai, 2022), the Big Data Maturity Model Radcliff (Radcliffe, 2014), the Maturity Model by Adrian (Adrian, Abdullah, Atan, & Jusoh, 2016), and A Value-Based Maturity Model (Farah, 2017).

The "Business Strategy" dimension is also relevant to several models. It appears in IBM's Big Data & Analytics Maturity Model (Nott, 2015), the Maturity Model for Big Data Development (Practitioner TNO, 2013, as cited in Al-Sai, 2022), and the Big Data Maturity Model Radcliff (Radcliffe, 2014). It is also part of A Maturity Model by Betteridge (Netteridge & Nott, 2014), A Value-Based Maturity Model (Farah, 2017), and the Maturity Model by Comuzzi (Comuzzi & Patel, 2016).

The "Organization" dimension is relevant to several frameworks. These include TDWI's Big Data Maturity Model (Halper & Krishnan, 2014), the Big Data Business Maturity Model Index (Practitioner EMC, 2013, as cited in Al-Sai, 2022), and the Big Data Maturity Framework / El-Darwiche Model (El-Darwiche et al., 2014). It is also identified in the Big Data Maturity Model Radcliff (Radcliffe, 2014), the Big Data Maturity Hortonworks 2016 Model (Dhanuk, 2016), the Maturity Model by Adrian (Adrian et al., 2016), and the Maturity Model by Comuzzi (Comuzzi & Patel, 2016).

The "Data Governance" dimension appears in Gartner's Data Maturity Model (Gartner, 2018), IBM's Big Data & Analytics Maturity Model (Nott, 2015), and TDWI's Big Data Maturity Model (Halper & Krishnan, 2014). It is also found in the Big Data Maturity Assessment Model by Knowledgent (as cited in Al-Sai, 2022), the Big Data Maturity Model Radcliff (Radcliffe, 2014), A Maturity Model by Betteridge (Netteridge & Nott, 2014), and the Maturity Model by Comuzzi (Comuzzi & Patel, 2016).

Lastly, the "Data Analytics" dimension is also relevant to several models. It is present in Gartner's Data Maturity Model (Gartner, 2018), IBM's Big Data & Analytics Maturity Model (Nott, 2015), and TDWI's Big Data Maturity Model (Halper & Krishnan, 2014). It also appears in the Maturity Model for Big Data Development (Practitioner TNO, 2013, as cited in Al-Sai, 2022), the Big Data Maturity Assessment Model by Knowledgent (as cited in Al-Sai, 2022), and the Big Data Maturity Model Radcliff (Radcliffe, 2014). Further, it is found in A Maturity Model by Betteridge (Netteridge & Nott, 2014), the Big Data Maturity Hortonworks 2016 Model (Dhanuk, 2016), and A Value-Based Maturity Model (Farah, 2017).

Findings from the expert's perspectives

In terms of the most prominent themes, in the interviews with experts, the Word Cloud presented in Figure 2, visually represents the findings. Larger words suggest higher frequency or importance, while smaller words appear less frequently. The most frequently mentioned words are "data," "decision," "network," "making," "service," and "quality," indicating a strong focus on data-driven decision-making, network infrastructure, and service quality in the telecom industry. Words like "analytics," "predictive," "optimization," "privacy," "storage," and "governance" are also frequently mentioned from the experts.

Figure 2. Prominent themes in the word cloud

Note. The word cloud has been filtered to remove non-relevant conjunctions.

The frequency analysis of interview codes revealed the codes that were most frequently mentioned, and probably most relevant to the Big Data maturity in the telecommunications sector. The most frequently mentioned aspect was data-driven decision-making, cited in 31 cases, followed by data analytic capabilities in 26 cases and human resources in 23 cases. Other significant areas included services in 22 cases, business strategy in 19 cases, prediction in 16 cases, data protection in 14 cases, network maintenance in 13 cases, innovation in 13 cases, sales in 12 cases, marketing in 10 cases, and big data policies in 11 cases. Topics related to network, were also discussed, with operations mentioned in 10 cases, network maintenance in 13 cases, network monitoring in 8 cases, network modernization in 8 cases, and network support in 7 cases. Network planning and optimization were noted in 3 cases, while engineering and field maintenance appeared in 2 cases each. Fraud detection was one of the least mentioned aspects, appearing in only 1 case. Data governance was also highly mentioned, with data quality mentioned in 13 cases, data protection in 14 cases, big data policies in 11 cases, data collection in 7 cases, data reliability in 4 cases, and data heterogeneity in just 1 case. Investments in data infrastructure were mentioned in 9 cases, while data storage appeared in 6 cases. However, data infrastructure investment was mentioned in only 2 cases. Topics related to Costumers, were less discussed, with customers mentioned in 21 cases, but specific aspects such as customer churn prevention (2 cases), customer behavior (1 case), and customer demographics (1 case) received even lower attention. In the same way targeted marketing, price optimization, and recommendation engines were each mentioned only once, by the experts participating in this research study.

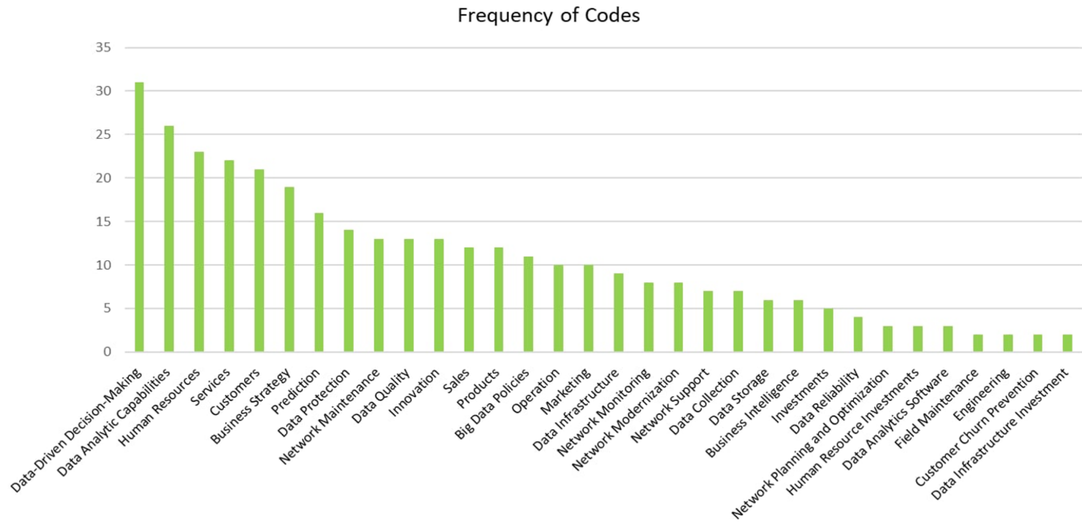

Figure 3. Frequency of codes
Note. Only codes mentioned more than once are presented in this graph.

With the aim of understanding the relationship between codes, the co-occurrence analysis was performed. This analysis presented in Figure 4, revealed many relationships between codes. Data-driven decision-making co-occurred with business strategy in three cases, emphasizing the strategic importance of using data for decision-making. Similarly, human resources co-occurred with data analytic capabilities in five cases, emphasizing the critical role of skilled personnel in implementing data-driven strategies. Network performance and network monitoring, co-occurred in four cases, suggesting an operational link between infrastructure efficiency and continuous monitoring. The repeated association between business strategy and data analytic capabilities further emphasized the importance of advanced analytics in shaping organizational strategy. The co-occurrence of these codes, has informed the process of codes network creation, elaborated in the next section.

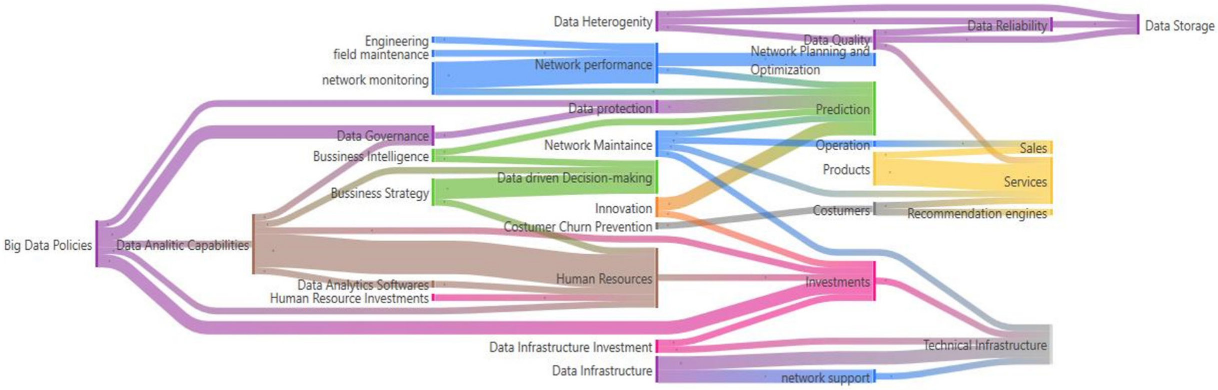

Figure 4. Codes co-occurrence
Note. This graph illustrates the co-occurrence of the same codes, showing how frequently they appear together.

Codes were further organized into groups to identify potential dimensions and subdimensions of the Big Data Maturity Model tailored for the telecommunications sector. To achieve this, a network of codes was created to explore the relationships among the identified codes. The process of codes network creation, was informed by the statistics of the co-occurrence analysis, findings from the literature review, and based on the logical relationships between the codes, which were established based on their conceptual similarities and shared meanings. This process was especially important for defining the most relevant dimensions and subdimensions of the maturity model by visually mapping how different concepts and themes interconnect. The network of codes is presented below, in the Figure 4,

illustrating the relationships among the codes and providing information into the potential structure of the framework aimed to be developed.
The code of Data Governance was associated with the codes of Big Data Policies, Data Heterogeneity, Data Infrastructure, Data Storage, Data Reliability, Data Collection, Data Quality, and Data Protection, ensuring secure and effective data management. The code of Fraud Detection was specifically linked to Data Protection, as it is a part of it. The code of Network Performance was associated with the codes of Network Planning and Optimization, Field Maintenance, Engineering, Operation, Network Monitoring, Network Support, and Network Maintenance, with Network Monitoring specifically linked to Network Support, as it plays an important role in ensuring its effectiveness. The code of Customers was associated with the codes of Customer Behavior, Customer Migration, Customer Demographics, and Customer Churn Prevention, and Customer Behavior. The code of Sales was associated with Targeted Marketing, Recommendation Engines, Price Optimization, Services, and Products, with Recommendation Engines and Price Optimization, specifically linked to Targeted Marketing, as they are relevant with personalized recommendations for customers. The code of Business Strategy was associated with Business Intelligence, Data-Driven Decision-Making, and Prediction. Data Infrastructure Investments and Human Resource Investments were linked with the code of Investments. The code of Network Modernization was associated with Innovation, as advancements in technology are as a result of innovative efforts and skills. The code of Data Analytic Capabilities was associated with Data Analysis Software and Human Resource Analytic Capabilities.

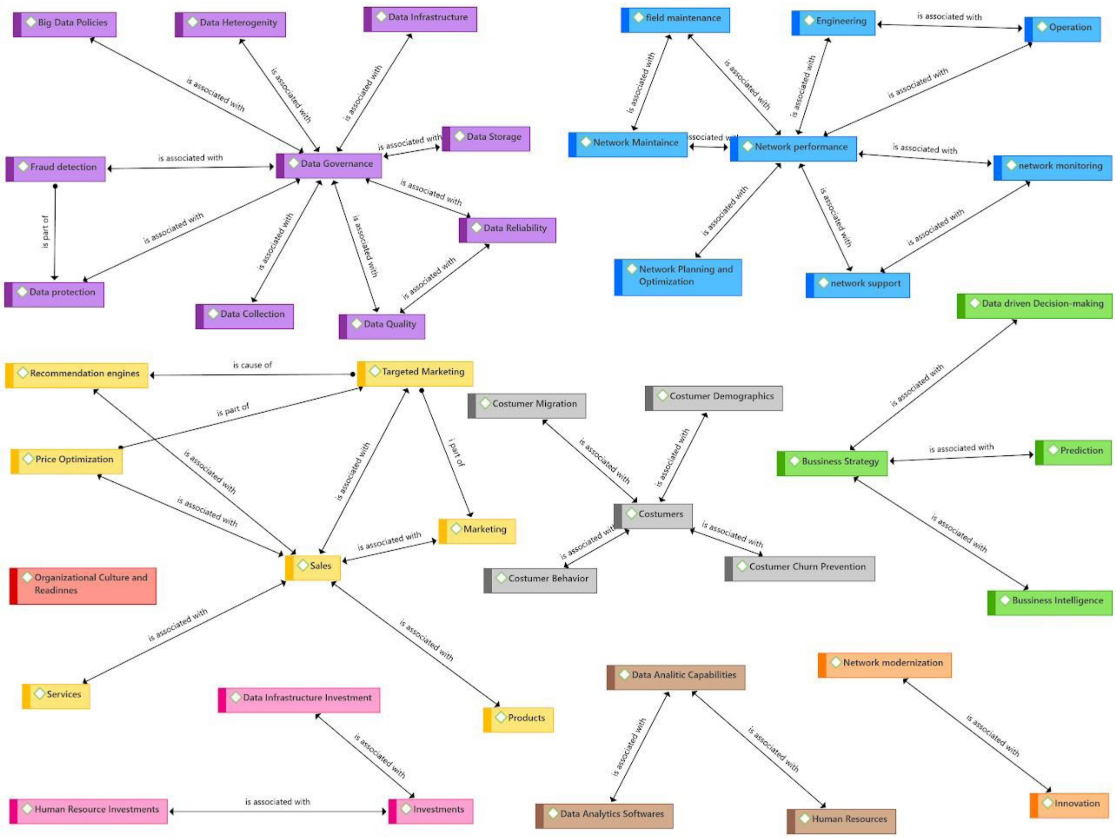

Figure 5. Network of codes
Note. This figure visualizes the relationships and connections between codes

As Telecom industry experts placed greater emphasis on network performance, with 40 mentions compared to 28 from academic experts. They also focused more on data analytics capabilities, which were mentioned 28 times, while academic experts mentioned them 20 times. Investments were significantly more emphasized by industry experts, with 9 mentions compared to only 1 from academic experts. Network modernization was mentioned 13 times by industry experts, while academic experts mentioned it 8 times. Additionally, organizational culture was noted only by industry experts, with 1 mention, while academic experts did not mention it at all.

In contrast, telecom academic experts placed more emphasis on data governance, mentioning it 45 times, compared to 25 mentions by industry experts. They also focused more on customers, with 15 mentions, while industry experts mentioned them 10 times. Business strategy was mentioned more by academic experts, with 28 mentions compared to 24 by industry experts. Similarly, sales received more attention from academic experts, with 28 mentions, while industry experts mentioned it 26 times.

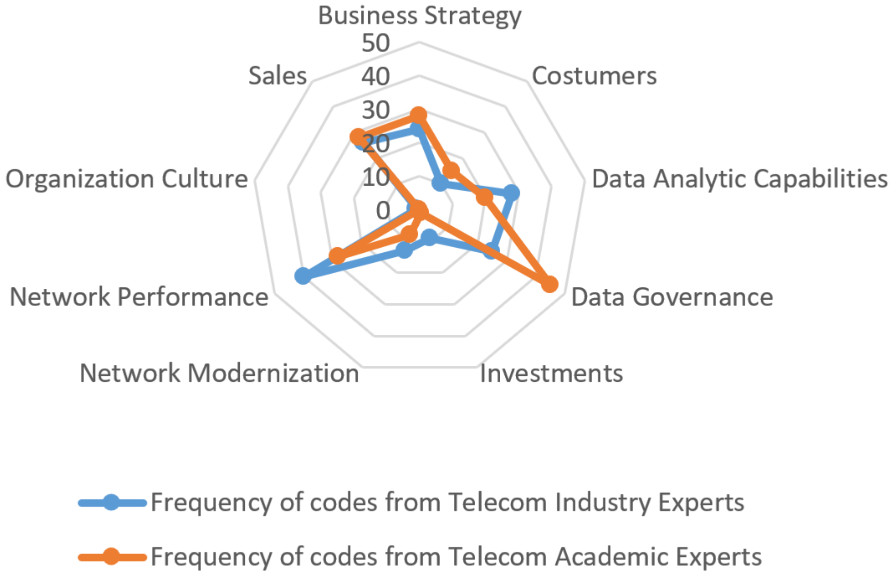

Figure 6. Code frequency divided by telecom academic and industry experts
Note. This figure compares the frequency of codes mentioned by telecom academic experts versus industry experts.

After establishing the network of codes, codes co-occurrence analysis and understanding the inputs from the telecom industry experts as well as telecom academic experts, the identified codes were systematically grouped into potential dimensions and sub- dimensions, in a logical based relationship and summarization, to structure the Big Data Maturity Model for the telecommunications sector. The Network Performance code is treated as a dimension and includes the following sub dimensions: Network Planning and Optimization, Field Maintenance, Operation, Network Support, Network Monitoring, Network Maintenance, and Engineering. The Data Governance code is treated as a dimension that includes the following sub dimensions: Data Quality, Data Heterogeneity, Big Data Policies, Data Protection, Fraud Detection, Data Infrastructure, Data Storage, Data Collection, and Data Reliability. The Customer code is treated as a dimension that includes the following sub dimensions: Customer Migration, Customer Churn Prevention, Customer Behavior, and Customer Demographics. Market Strategy was used as a term that best represents the dimension that includes the following sub dimensions: Targeted Marketing, Price Optimization, Recommendation Engines, Sales, Marketing, Services, and Products. Business Development was used as a term that best represents the dimension that includes the following subdimensions: Data-Driven Decision-Making, Prediction, Business Strategy, and Business Intelligence. The Data Analytics Capabilities code is treated as a dimension that involves the sub dimensions Data Software Analytics and Human Resource Analytics Capabilities. The Network Modernization code is treated as a dimension and includes only Innovation as its sub-dimension. The Investments code is also treated as a dimension and includes the following sub-dimensions: Data Infrastructure Investments and Human Resource Investments. The Organization code is classified as a dimension but does not have any defined sub-dimensions.

To develop the Big Data Maturity Model tailored to the telecommunications sector, dimensions identified from two sources were systematically combined: findings from generic Big Data Maturity Models and findings derived from expert interviews conducted for this paper. From the analysis of generic models, five key dimensions were identified as essential for incorporation into the proposed framework: Data Management, Business Strategy, Organization, Data Governance, and Data Analytics. These dimensions were selected based on their frequent occurrence across multiple models, ensuring their relevance to assessing Big Data maturity. In parallel, findings from expert interviews provided more detailed information into the operational and strategic aspects of Big Data in telecommunications. The interviews emphasized additional critical dimensions, including Network Performance, Network Modernization, Investments, Market Strategy, Customers, Data Analytic Capabilities and Organizational Culture.

To create a unified framework, the generic and interview-derived dimensions were integrated as follows: “Data Governance” and “Data Analytics” from the generic models aligns with the existing findings from the interviews. “Data Management” from the generic model, is treated as a sub-dimension of Data Governance, based on the findings from the interviews. “Business Strategy” from the generic model, is treated as a sub-dimension of the “Business Development” dimension. While, “Organization” from the generic models stands as a specific dimension, with “Organization Culture” from the findings from interviews as a sub dimension.

The integration process resulted in the identification of ten key dimensions for the Big Data Maturity Model tailored for the telecommunications sector. These dimensions include: Data Governance, Business Development, Data Analytic Capabilities, Network Performance, Network Modernization, Investments, Market Strategy, Customers and Organization. Together, these dimensions create the proposed comprehensive framework to evaluate Big Data maturity in telecommunications.

Table 2: Core framework of the Big Data Maturity Model: Dimensions and Sub dimensions

Dimension	Sub dimensions
Data Governance	Data Quality Data Heterogeneity Big Data Policies Data Protection Data Infrastructure Data Storage Data Collection Fraud Detection Data Reliability
Market Strategy	Products Services Marketing Sales Recommendation Engine Price Optimization
Network Performance	Strategic Marketing Network Planning and Optimization Field Maintenance Operations Network Support Network Monitoring Engineering Network Maintenance
Business Development	Business Strategy Business Intelligence Prediction Data-Driven Decision-Making
Customers	Customer Demographics Customer Behavior Customer Churn Prevention Customer Migration
Data Analytics Capabilities	Data Software Analytics Human Resource Analytics Capabilities
Investments	Data infrastructure Investments Human Resource Investments
Organization	Organizational Culture
Network Modernization	Innovation

DISCUSSION

The findings of this paper on the Big Data Maturity Model for the telecommunications industry are in line with existing literature, confirming the relevance of several dimensions and subdimensions with the proposed Big Data maturity model tailored for telecommunication companies. A review of the most frequently identified dimensions across 17 generic Big Data maturity models, combined with findings from 10 expert interviews, resulted with the identification of 10 key dimensions relevant to the telecommunications industry. These dimensions help organizations improve their Big Data maturity level. They include Data Governance, Business Development, Data Analytic Capabilities, Network Performance, Network Modernization, Investments, Market Strategy, Customers, and Organization, each of which contains relevant sub-dimensions as shown in Figure 7. The dimension of Data Governance is an important aspect considered in the relevant literature. Otto (2011) categorizes data governance in telecommunications into three different domains: 'Organizational Goals, Organizational Form, and Organizational Transformation. The first subset, Organizational Goals, refers to the formal and functional objectives of the organization, which guide Big Data initiatives. The second domain, Organizational Form, includes the activities necessary to achieve business objectives, while the third domain, Organizational Transformation, focuses on the processes of transformation and organizational change.

Moreover, the Business Development dimension, which includes elements like data-driven decision-making and business intelligence, plays an important role in transforming the way telecom companies operate. Krasic, Celar, and Seremet (2021) note that Business Intelligence systems enable decision-making based on data, providing telecom companies with the tools needed to improve strategic decisions and therefore, their organizational performance.

In one of their studies, Zahid et al. (2019), have investigated the literature related to Big Data Analytics in the sector of telecommunication. According to them, Big Data Analytics is highly important for the telecommunications industry, yet its practical applications in academic research remain limited due to gaps in architecture and the use of emerging technologies. To address this, they propose "LambdaTel", a 'lambda architecture designed to provide a structured framework for implementing BDA in telecom', which has been successfully implemented in one case by the authors.

According to Samaan and Jeiad (2023) Network Performance as an important aspects of the telecommunication companies, might highly benefit from the use of big data. They revealed that by applying predictive analytics, telecommunication operators can anticipate possible failures in the network performance and take proactive measures to prevent them. These finding support the dimension of the Network Performance.

Sadiku, Adekunte, and Sadiku (2024) further elaborated on the areas that benefit most from Big Data usage, such as "Customer Experience, Network Optimization, Operational Analysis, Data Monetization, Fraud Detection, Price Optimization, Customer Churn Prevention, and Product Development". These applications align with the findings of this paper, emphasizing the multi-dimensional impact of Big Data on telecom organizations' strategic performance. The subdimension of Innovation, as part of the Network Modernization dimension, is supported by Al-Jaafreh and Fayoumi (2017). They have pointed out that organizations in the telecom sector can become more innovative by using Big Data technologies, 'driving process improvements, and increasing agility in decision-making'.

The dimension of Investments, which includes human resource investments and data infrastructure investments, plays a significant role in the adoption of Big Data in the telecommunications sector. This is supported by Bughin (2016), who suggests that telecom companies allocate a portion of their workforce and capital expenditures to Big Data initiatives, with an average expenditure "of 1.1% of revenue on labor costs and 0.9% on capital investments". Bughin (2016) also reports that '72% of companies investing in Big Data have launched applications in customer-facing domains, such as marketing, sales, fraud prevention, retention, and services', underscoring the importance of targeted investments in Big Data for driving service improvement and competitiveness. Moreover, Lim, Richardson, and Roberts (2004) confirmed that investments in big data are positively linked with firm performance. Similarly, Jekov, Petkova, Gotsev, and Petkova (2021) support the positive impacts of targeted marketing, predicting churn, and customer satisfaction as key benefits derived from Big Data analytics in telecom.

The Customers dimension, with sub dimensions related to Customer Behavior, has been supported by several studies. Singh and Singh (2017) emphasized that the telecommunications industry could benefit from big data to better understand customer behavior and provide personalized offerings and services. According to them, this is also related to marketing strategies. This aligns with the Market Strategy dimension and its relevant sub dimensions, including Targeted Marketing, Recommendation Engines, and Price Optimization.

The findings of this paper contribute to the existing knowledge on Big Data in the telecommunications industry by suggesting the first big data maturity model tailored for this industry. By integrating the findings from existing maturity models and expert interviews, this paper identifies the most relevant dimensions and subdimensions that are relevant to the Big Data Maturity Model tailored for the telecommunications industry. The results show that the most relevant dimensions are: data governance, business development, network performance, customer, market strategies, organization, data analytic capabilities and investments. Furthermore, this research points out the need for a framework to assess Big Data maturity, ensuring that telecom companies can effectively engage in the decision-making processes based in data. Future studies could further provide inputs in the relevance of these dimensions and suggest other aspects that would complement the framework.

CONCLUSION

In the beginning of this paper, two research questions were posed. The first question focused on identifying the essential dimensions that a Big Data Maturity Model in the telecommunications industry should include. The second question aimed to identify the key sub-dimensions for each of these dimensions.
The findings of this paper derived after identifying the most frequent dimensions across 17 generic Big Data maturity models and analyzing the perspectives of 10 expert interviews. These findings suggest several dimensions that are relevant for evaluating Big Data maturity in telecommunications organizations. The identified dimensions are: Data Governance, Business Strategy, Data Analytic Capabilities, Network Performance, Network Modernization, Investments, Sales, Customers, and Organization. Together, these dimensions create a framework to assess Big Data maturity in the telecommunication industry.
In terms of sub-dimensions, each dimension has specific areas contributing to its development. For instance, Network Performance includes sub dimensions such as network planning and optimization, and network monitoring, while Data Governance include data quality, data heterogeneity, big data policies, and data protection. The Customers dimension includes aspects like customer migration and churn prevention, and Sales incorporates targeted marketing, price optimization, and recommendation engines. Other dimensions, such as Business Strategy, include data-driven decision-making and business intelligence as sub dimension, while Network Modernization includes innovation and network upgrades. Investments cover human resource investments and data infrastructure investments, and Data Analytic Capabilities focuses on data analytics software and human resources. The Dimension Organization does not have defined sub-dimensions; however, areas like values, leadership, communication, culture and collaboration may be explored to further define this aspect in the future studies. Together, these dimensions and sub-dimensions provide a structured approach of a core framework, for organizations in the telecommunications industry to assess their Big Data maturity and strategically improve their capabilities to further improve their performance and decision-making.

Conflict of Interest

No potential conflict of interest was reported by the authors.

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ADOPTING LITHUANIA'S CIRCULAR ECONOMY BLUEPRINT: A DATA-DRIVEN ROADMAP FOR ALBANIA'S WASTE POLICY.

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Abstract

This study examines how Albania can meet EU environmental standards by shifting municipal solid waste (MSW) management from landfilling toward circular economy practices, using Lithuania's 2014–2023 trajectory as a benchmark. It applies a mixed-methods analytics framework, including K-Means clustering to reveal distinct waste-management regimes, STL decomposition to separate long-term trends from seasonal noise, and regression-based scenario simulation to project policy impacts. Over the last decade, Lithuania has reduced its landfill rate from approximately 60% to under 8% and more than doubled its recycling rate, fully aligning with EU waste directives. In contrast, Albania remains at roughly 75% landfilling, although our analysis detects nascent improvements linked to early policy reforms and socioeconomic shifts. Clustering highlights two performance groups high-landfill versus high-recovery regimes while STL analysis clarifies the timing and magnitude of policy-driven inflection points. Scenario simulations suggest that, under accelerated EU-aligned interventions (e.g., deposit–return schemes, extended producer responsibility), Albania could halve its landfill share within five years and achieve EU recycling targets by 2030. These findings offer a data-driven roadmap for accession countries: by adopting Lithuania's proven mix of regulatory measures, infrastructure investments, and public outreach, Albania can transition more rapidly toward a circular economy.

Keywords: Municipal solid waste management; Circular economy; Landfill reduction; K-means clustering; Time-series analysis; EU accession; Waste management policy

1. INTRODUCTION

1.1 Motivation & Objectives

Municipal solid waste management is a significant challenge for countries in transition, where rapid urbanization and economic growth often outpace the development of infrastructure. In Albania, more than 75 % of household and commercial waste is still deposited in landfills or informal dumpsites many of which lack proper liners or leachate controls, leading to soil and water contamination and significant methane emissions (European Environment Agency, 2021a).

At the same time, the European Union has set a clear mandate: under Directive 1999/31/EC (Landfill Directive) and its 2018 amendment (Directive 2018/850), member states must reduce the share of municipal waste landfilled to 10 % or less by 2035, with an aspirational interim target of 10 % by 2030;(Council of the European Union, 2018) this goal is reinforced by the Waste Framework Directive 2008/98/EC's hierarchy that prioritizes prevention, reuse, and recycling over disposal (Council of the European Union, 2008)

Lithuania an EU country with a population size comparable to Albania's offers a striking example of what concerted policy action and investment can achieve. Between 2014 and 2023, Lithuania cut its landfill rate from approximately 60 % down to under 8 %, driven by nationwide deposit-return schemes for beverage containers, expansion of separate collection and recycling facilities, and the deployment of modern waste-to-energy plants for residual streams (Eurostat, 2025a) (European Environment Agency, 2025a)

Lithuania was selected as the comparative case in this study due to its demographic and economic similarities to Albania, its status as a EU member state, and its successful transformation from landfill dependency to a circular-economy model within a single decade.(European Environment Agency, 2025a). This makes Lithuania a relevant and realistic benchmark for Albania's own transition, especially in the context of aligning with EU waste directives and circular economy targets.

These measures not only drove down landfill volumes but also generated high-quality secondary materials and energy, embodying the circular-economy principles promoted by Brussels. This paper addresses a central question: How can Albania replicate Lithuania's success to meet EU landfill-reduction targets and transition toward a circular economy? Our specific objectives are: Quantitative comparison of Albania's and Lithuania's municipal waste trajectories (2014–2023), focusing on landfill

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and recovery rates. Application of big-data analytics including unsupervised clustering, time-series decomposition, and regression-based scenario simulation to uncover patterns, regime shifts, and the impact of socioeconomic factors on landfill disposal. Development of evidence-based recommendations for policy, economic incentives, and technological investments to guide Albania's waste-management reform in line with EU accession requirements.

1.2 Structure

To guide the reader through our analysis, the paper is organized into six sections. Section 1 introduces the policy challenge of municipal waste management in Albania and frames Lithuania as a comparative benchmark. Section 2 reviews relevant EU waste-management legislation and Lithuania's transition to a circular-economy model. Section 3 details the empirical methods employed, including data preparation and three analytic techniques: K-Means clustering to explore waste-regime groupings, STL decomposition to analyze long-term trends in landfill use, and multivariate regression with scenario simulation to assess the influence of recovery, urbanization, and economic conditions on landfill outcomes. Section 4 presents the results from each technique, drawing contrasts between Albania's and Lithuania's trajectories. Section 5 interprets the findings in the context of national policy reforms, identifying key leverage points for Albania. Section 6 concludes by offering actionable recommendations and summarizing insights to inform Albania's path toward EU-aligned waste reduction.

2. LITERATURE REVIEW

2.1 EU Landfill & Waste Framework Directives

Since its adoption in 1999, Council Directive 1999/31/EC has provided the EU's foundational framework for municipal waste landfilling. Its primary aim is "to ensure a progressive reduction of landfilling of waste, in particular of waste that is suitable for recycling or other recovery, and, by way of stringent operational and technical requirements on the waste and landfills, to provide for measures, procedures and guidance to prevent or reduce as far as possible negative effects on the environment ... and any resulting risk to human health" (Council of the European Union, 2018).

From the outset, Member States have been required to obtain permits for new and existing sites, apply uniform waste-acceptance criteria, install engineered liners and leachate-collection systems, control landfill gas, and report annually in a harmonized format on the quantities and types of waste disposed (Council of the European Union, 2018)

Recognizing that a fully circular economy demands ever tighter limits on disposal, Directive (EU) 2018/850 amended 1999/31/EC to reinforce its objectives and align terminology with the Waste Framework Directive 2008/98/EC. The amendment explicitly invokes the waste-hierarchy principles of Article 4 (prevention → preparing for re-use → recycling → recovery → disposal) and the end-of-waste/by-products criteria of Article 12 of the 2008 Directive, while preserving the call for "prudent, efficient and rational utilization of natural resources". (Council of the European Union, 2018)It also standardizes definitions of "waste," "recycling," "recovery," and "preparing for re-use" to eliminate inconsistencies across the acquis. (Council of the European Union, 2018)

The most consequential changes in the 2018 amendment appear in Article 5 and the new Article 5a. From 1 January 2030, the landfilling of any waste suitable for recycling or other recovery will be prohibited, unless recovery would result in a clearly better overall environmental outcome. (Council of the European Union, 2018)Furthermore, by 31 December 2035, the weight of municipal waste sent to landfill must not exceed 10 % of the total generated, with a possible five-year extension for Member States that landfilled over 60 % in 2013, subject to a detailed implementation plan. (Council of the European Union, 2018) To ensure timely corrective action, the Commission in collaboration with the European Environment Agency will issue "early-warning" reports at least three years before each deadline to identify shortfalls and recommend measures. (Council of the European Union, 2018)

Article 5a further strengthens the regime by mandating that "only waste that has been subject to treatment to comply with the waste-acceptance criteria may be landfilled," thereby preventing unprocessed or inadequately treated materials from entering disposal. (Council of the European Union, 2018).It also requires Member States to develop and implement national strategies aimed at progressively reducing the quantity of biodegradable municipal waste going to landfill, reflecting the distinct environmental risks posed by organic fractions. (Council of the European Union, 2018). Together, these provisions build on the Waste Framework Directive's hierarchy and establish a comprehensive, legally binding pathway toward minimal reliance on landfilling. Although several Member States such as Germany, Austria, and Sweden already meet the 10 % target through robust recycling, composting, and waste-to-energy infrastructures. (Eurostat, 2025b), others lag significantly, underscoring the directive's role in driving convergence toward a circular-economy model across the Union.

2.2 Lithuania's Landfill Reduction & Circular-Economy Measures

Lithuania's transformation from a landfill dependent system into an emerging circular economy model rests on a combination of infrastructure expansion, regulatory measures, economic incentives, and strategic planning. (European Environment Agency, 2025b)

First, over the past decade Lithuania has achieved a dramatic decline in its municipal waste landfill rate, from over 50 % in 2010 to just 14 % in 2022. This shift reflects the parallel rise in energy recovery: incineration with energy recovery climbed from virtually 0 % in 2010 to 38 % by 2022. A pivotal moment occurred in 2016, when ten new mechanical biological treatment (MBT) facilities came online, significantly boosting composting and digestion outputs; by 2020, two major incineration plants increased thermal treatment capacity from 255 000 t/yr to 615 000 t/yr, allowing residual waste to be diverted from landfill into energy recovery. (European Environment Agency, 2023)

Second, Lithuania's regulatory framework imposes both bans and pricing signals to discourage disposal. Since 2013, untreated municipal waste and biodegradable fractions have been prohibited from landfill, and landfill tax rates have steadily escalated from €10 /t in 2021 to €15 /t in 2022, reaching an inflation indexed €70.20 /t in 2023, among the highest in the EU. No equivalent tax burdens energy recovery, further tilting the economics in favor of recycling and incineration. (European Environment Agency, 2025b)

Third, mandatory separate collection systems now cover virtually the entire population. While in 2010 about 6 % of Lithuania's population lacked formal municipal waste coverage, by 2019 over 99 % of the territory urban and rural enjoyed either door to door or "bring point" services for paper, glass, metals, plastics, bio waste and other streams. As of 2023 bio waste collection is universal, with textile collection mandated by 2025, ensuring high quality feedstocks for treatment facilities. (European Environment Agency, 2025b)

Fourth, extended producer responsibility (EPR) schemes and deposit return systems secure clean secondary raw material streams. Lithuania's EPR covers all packaging streams paper, glass, metals, plastics and wood with fee modulation to reward recyclability, and a deposit return scheme for beverage containers ensures high capture rates of pure materials. (European Environment Agency, 2023, 2025b)

Finally, Lithuania has embedded waste management reforms within its broader circular economy strategy. The National Waste Prevention and Management Plan 2021–2027 (approved July 2022) is explicitly integrated into the forthcoming National Action Plan for the Circular Economy (2023–2035), a roadmap covering eco-design, secondary material use, repair services, and innovative sharing platforms. Despite these advances, Lithuania's circular material use rate remains low (4.4 % in 2020 versus an EU average of \~13 %) , highlighting ongoing opportunities to deepen material loop closure. (European Environment Agency, 2023)

Together, these measures state-of-the-art treatment capacity, stringent bans and taxes, universal collection, producer accountability, and cross-sector circular-economy planning form a coherent strategy that has driven Lithuania's landfill rate well below the 10 % EU target and offers a blueprint for Albania's own transition. (European Environment Agency, 2023, 2025b; Eurostat, 2025b)

2.3 Big-Data Analytics Applications in Waste Management

Big-data analytics is transforming municipal waste management by uncovering hidden patterns, isolating temporal effects, and quantifying key drivers. Three core methods clustering, Seasonal-Trend decomposition using LOESS (STL), and regression have proven especially impactful. Clustering algorithms (e.g., K-Means) delineate areas with similar waste generation behaviors, enabling optimized collection routes and targeted interventions (Gunaseelan et al., 2023; Kuzhin et al., 2024). STL decomposition then teases out long-term trends and irregular "seasonal" bumps such as spikes around holidays or policy rollouts improving forecasts of waste volumes, regression analysis links socioeconomic variables (population density, GDP, urbanization) to waste outputs, allowing scenario-based projections under different policy mixes (Allesch & Brunner, 2015; Mahalakshmi, 2023). In our comparative framework, these methods reveal how Lithuania's calibrated analytics-driven interventions yielded dramatic landfill reductions lessons Albania can adapt to accelerate its circular-economy transition.

3. METHODOLOGY

3.1 Data Sources & Preprocessing

This study uses annual data from 2014 to 2023 for Albania and Lithuania, sourced from Eurostat(Eurostat, 2025b; and the World Bank. Waste statistics such as total generated, landfilled, and recovered through recycling or energy came from Eurostat, while socioeconomic indicators like GDP (constant 2015 USD), urbanization, unemployment, and population were taken from the World Bank's World Development Indicators. From this data, were calculated two key performance metrics: (World Bank Group, 2025)

- Landfill rate = (landfilled waste ÷ total waste generated) × 100
- and recovery rate = (recycled + energy-recovered waste ÷ total waste generated) × 100

These were computed for each country and year, ensuring consistency across values. Before analysis, all variables were merged by year and country, and continuous features were standardized (mean zero, unit variance). This step ensured fair comparison across variables measured in different units. The dataset was complete no missing values so no imputation was needed.

While the dataset covers only two countries over a 10-year period, this limited scope was intentionally chosen to enable a focused comparative case study. Albania and Lithuania present contrasting waste-management outcomes under differing policy environments, yet share comparable population sizes and regional relevance. The objective is not broad generalization but to extract targeted policy lessons that can guide Albania and similar EU candidate countries through their transition to a circular economy.

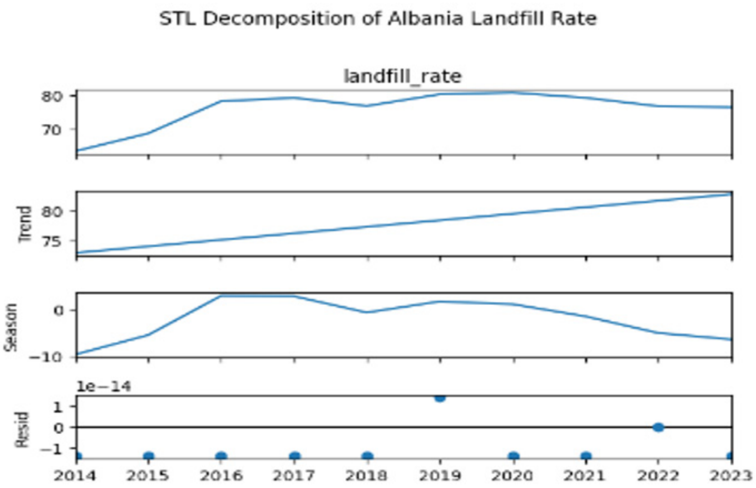

Figure 1 - STL Decomposition of Albania Landfill Rate

3.2 Clustering Analysis

K-means clustering was used to explore patterns in waste management performance. (MacQueen, 1967, Scikit-learn developers, 2024) on country-year data from Albania and Lithuania (N = 20). The analysis included five features: landfill rate, recovery rate, GDP, urban population share, and unemployment. All features were standardized to avoid bias from differences in scale.

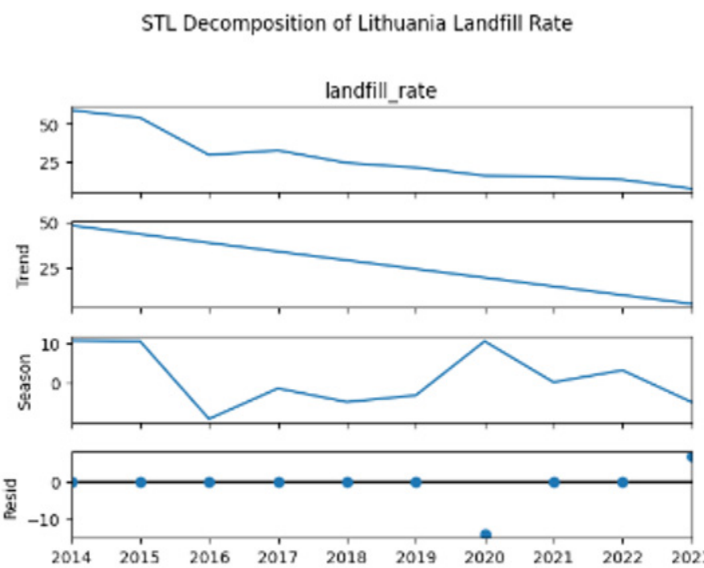

Figure 2 - STL Decomposition of Lithuania Landfill Rate

Cluster solutions were tested for k = 1 to 6 and used the elbow method to find the best fit. The sharpest drop in within-cluster variance occurred at k = 2, so it was chosen a two-cluster model for its simplicity and clarity.

We assigned each country–year observation to one of two clusters, reflecting distinct waste management regimes. Clustering was applied to the combined dataset to help position Albania relative to Lithuania not to generalize findings across other countries. Final interpretations were made using the original (unscaled) data for easier understanding.

3.3 Time-Series Decomposition

To uncover long-term trends in landfill usage, it was applied STL (Seasonal-Trend Decomposition using Loess) to the annual landfill-rate data for Albania and Lithuania. STL breaks each time series into three parts: a trend (long-term movement), a seasonal component (cyclical variations), and a residual (random noise).

As the data are annual, the seasonal component largely represents multi-year cycles rather than true seasonality. We ran the decomposition separately for each country using the same settings, allowing for a fair comparison of how landfill reliance has changed over time.

3.4 Regression Modeling

After the clustering and trend analysis, it was used an ordinary least squares (OLS) regression to explore what drives landfill rates (Cleveland, 1990). Our outcome variable was the landfill rate, and included five predictors: recovery rate, GDP (in constant 2015 USD), urban population share, unemployment rate, and a post-2019 binary indicator (1 for 2020–2023, 0 otherwise). These binary indicator captures broad shifts after 2019 such as new EU directives, Albania's 2020 waste plan, or COVID-19 disruptions that may have influenced landfill trends (European Environment Agency, 2021b).

Socioeconomic factors were included to account for differences in infrastructure and economic conditions. For example, wealthier or more urbanized areas might divert more waste away from landfills, while high unemployment could limit investment in waste systems (Hoornweg, 2012) All continuous variables were standardized for comparability; the binary indicator was left as a 0/1 indicator.

The model was run on the full dataset (20 observations from both countries over 10 years) using Python's Statsmodels package. Given the small sample size, HC3 robust standard errors were used to adjust for possible heteroskedasticity. (Seabold & Perktold, 2010) Model diagnostics showed no major issues residuals were normal, and multicollinearity was within acceptable limits. These regression results formed the basis for the scenario simulations that follow.

3.5. Monte Carlo Simulation

The scenario analysis compared Albania's predicted landfill rates in 2023 under two cases: the status quo and a modest improvement. In the baseline, using Albania's actual 2023 data, the model predicted a landfill rate of about 75% very close to observed values. In a counterfactual scenario with a 10-point higher recovery rate and 5-point increase in urbanization, the predicted landfill rate dropped noticeably, to the mid-60s.

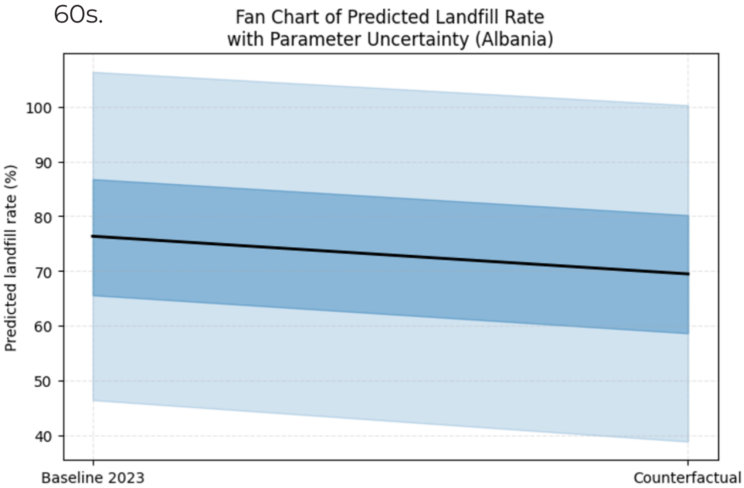

Figure 3 - Fan Chart of predicted landfill rate with parameter uncertainty (Albania)

A fan chart (Figure 3) illustrates these results, showing the distribution of predicted outcomes based on 5,000 simulated coefficient draws. The darkest blue band in the center represents the interquartile range (i.e., the middle 50 % of simulated predictions), highlighting where most outcomes are concentrated. The entire range of outcomes under the improved scenario shifts downward compared to the baseline, suggesting that even with uncertainty, better waste recovery and urban services would likely reduce landfill reliance. However, the decrease isn't enough to reach EU standards or Lithuania's levels. The chart underscores a key point: even modest reforms can help but larger, more systemic changes are needed for Albania to catch up.

4. DISCUSSION AND LIMITATIONS

This comparative analysis offers several insights into how Albania's waste management trajectory stands relative to a successful EU case (Lithuania) and in relation to broader policy targets. The findings demonstrate that Albania is still heavily reliant on landfilling as of 2023, in stark contrast to Lithuania's near-elimination of landfilling over the past decade. In the context of European waste policy, Albania's status quo is misaligned with the EU's long-term targets for landfill reduction. (Council of the European Union, 2025) For instance, the EU Landfill Directive and Circular Economy Package call for member states to sharply curtail municipal waste going to landfill (with a common target of max 10% of municipal waste to landfill by 2035). (Council of the European Union, 2025) Lithuania's observed trend dropping to under 10% landfill rate by 2023 shows that this level of performance is achievable under strong policy commitments and investments. Indeed, Lithuania's progress closely tracks the implementation of EU waste directives (such as increasing recycling quotas, landfill taxes/bans, and extended producer responsibility schemes) and benefitted from substantial EU structural funds for waste infrastructure. (European Environment Agency, 2025b) By contrast, Albania, which is a candidate for EU membership but was not an EU member during the study period, has not yet realized comparable improvements. The stagnation of Albania's landfill rate around 75–80% indicates that the policy measures and infrastructure investments seen in EU member states have not fully taken hold in Albania's case. Contributing factors likely include limited waste treatment infrastructure (few recycling facilities or waste-to-energy plants), weaker enforcement of waste separation and recycling programs, and financial or governance constraints that impede large-scale waste system upgrades. (Organisation for Economic Co-operation and Development (OECD), 2024) Additionally, public awareness and participation in recycling may be low in the absence of strong nationwide programs, further slowing progress. he divergence between the two countries' trajectories underscores a significant challenge for Albania: aligning its waste management practices with EU standards and moving toward a circular economy (see Section 2.3 for Lithuania's own transformation) will require not just gradual improvements but potentially transformative changes in policy, infrastructure, and behavior. Importantly, our results highlight that socioeconomic context and policy timing play a role in waste management outcomes. The regression analysis, while based on a small sample of two countries over a 10-year period, nonetheless reveals meaningful correlations, such as an inverse relationship between GDP, urbanization, and landfill reliance. This limited scope constrains statistical power and broader generalizability. However, the study was intentionally designed as a focused comparative case analysis between a transitioning EU candidate (Albania) and a successful EU member (Lithuania), both with similar population sizes and regional contexts. The goal is not to generalize across all countries but to offer a data-driven roadmap that other EU accession countries with comparable trajectories could adapt. It is also acknowledged that the use of a linear regression model simplifies the complex policy environment and may not capture nonlinear effects or implementation lags that often characterize real-world waste management reforms. Future work could address these limitations by applying more advanced techniques, such as panel models with fixed effects, lagged regression structures, or dynamic system modeling, to better reflect the temporal and nonlinear dynamics of policy impact. By contrast, economic stress (e.g., higher unemployment) is positively correlated with landfill reliance, suggesting that greater economic hardship makes it more difficult to divert waste from landfills.. This aligns with broader observations that wealthier, more developed societies invest more in environmental infrastructure and tend to have stronger institutions for waste management (Wilson et al., 2006) (Mazzanti & Zoboli, 2008). In Albania's case, continued economic development and urbanization could create more favorable conditions for improving waste systems, but these factors alone are not sufficient without targeted waste policies. The inclusion of the post-2019 binary indicator in our model was intended to capture shifts due to policy changes or other external shocks. The negative sign on this binary indicator (though not statistically definitive) is consistent with the timing of new waste management initiatives and EU-aligned policies coming into effect around 2020. For instance, Albania approved a National Waste Management Strategy and Plan around 2018–2020, aiming to improve recycling and reduce dumping (Ministry of Tourism and Environment of Albania, 2020) , and the EU's revised Waste Framework Directive and Single-Use Plastics Directive started to influence practices Europe-wide around that time (Council of the European Union, 2025). Moreover, the COVID-19 pandemic initially disrupted waste patterns but also led to some waste reduction and changes in consumption by 2020–2021. Our analysis suggests there may indeed have been a modest downward shift in Albania's landfill rate in recent years, but it is small relative to the overall level and could easily be obscured by data variability. Lithuania's membership in Cluster 1 (Figure 4) and its steep trend decline reflect not only its socioeconomic status but also deliberate policy action including early adoption of EU recycling targets, implementation of landfill bans on untreated waste, and the introduction of measures like deposit-refund systems for beverage containers (European Environment Agency, 2025b) . The stark difference in cluster assignment (Albania remaining in the "high landfill" cluster vs. Lithuania in the "low landfill" cluster by 2023) quantitatively emphasizes how far Albania is from the EU norm. This context implies that Albania must accelerate its transition if it is to meet future obligations and avoid being left with an outdated waste system. The strengths of this study lie in its multi-faceted methodological approach and its focused comparative design. By using clustering analysis, Albania's performance was framed in a broader context and confirm that it represents a distinct grouping associated with underdeveloped waste management, as opposed to Lithuania's grouping with advanced systems. The time-series decomposition added clarity by separating structural trends from noise, thereby illustrating the effectiveness (or lack thereof) of policies over time. The regression modeling provided a quantitative lens on which factors matter most, reinforcing the centrality of increasing recovery efforts. Finally, the Monte Carlo simulation translated those regression insights into a tangible scenario-based outcome, showing the possible range of improvements from achievable policy changes. This combination of techniques descriptive clustering, analytical decomposition, causal inference (regression), and predictive simulation offers a comprehensive picture of the issue. It also demonstrates an approach that can be applied to other country comparisons or expanded datasets in future research. However, there are important limitations to acknowledge. First, the analysis is constrained by the small sample (two countries, one decade), which limits statistical power. The regression results should be interpreted cautiously given the very low degrees of freedom; some coefficients that aligned with theory were not statistically significant, and there is the possibility of omitted variable bias or overfitting. A related limitation is that the data was effectively treated as pooled cross-sections, without explicitly modeling country-specific effects or time dynamics beyond the simple binary indicator a more sophisticated panel data approach (e.g. fixed effects or random effects models) could not be justified here due to the minimal number of panels (only two) and short time span. Second, the quality and definitions of data could influence results. The analysis relied on official Eurostat and WDI data, but there may be differences in how waste recovery is measured (especially for Albania) or unrecorded informal recycling activities that are not captured. If the underlying data are inconsistent or missing certain waste streams, that could affect the computed rates. Third, our scenario simulation focuses on parameter uncertainty in the regression and holds many factors constant; it does not capture the full uncertainty in real-world outcomes (for example, year-to-year fluctuations in waste generation or the exact trajectory by which improvements might be realized). Real policy changes often have implementation lags and nonlinear effects that are not reflected in our simple linear model. Additionally, the improved scenario was intentionally modest which is useful to gauge incremental change but it means it did not explore the full pathway needed for Albania to approach EU-level performance. A more aggressive scenario (e.g. Albania mirroring Lithuania's recovery rate jump) could be analyzed in future work, possibly using a broader simulation or systems modeling approach (Xu et al., 2020) . Lastly, while this study draws a comparison between one EU member and one aspiring member, the generalizability of the findings may be limited. Other countries have different starting conditions and policy environments; thus, the specific quantitative results here are most directly relevant to Albania's situation. The broader implication, however, is that significant policy intervention is required to alter the status quo of high

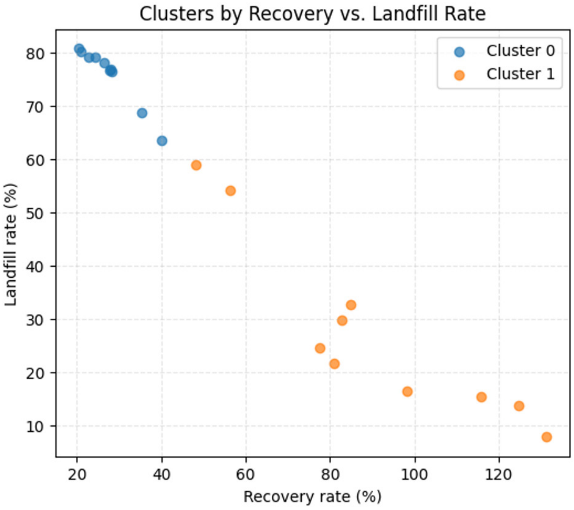

Figure 4 - Clusters by Recovery vs Landfill Rate

landfilling a point that likely holds in any context where landfill remains the dominant waste fate (Wilson et al., 2012). In the context of policy, our findings imply that merely maintaining current practices will not yield substantial change for Albania. Lithuania's experience shows that concerted efforts aligned with EU directives can rapidly drive down landfill usage. The discussion therefore points to a need for Albania to not only adopt similar measures but to adapt them to its local context. It also involves recognizing socioeconomic constraints: policies must be accompanied by capacity-building and public engagement to be effective. Overall, the comparison underscores that moving toward a circular economy is a multi-dimensional challenge that requires aligned action on regulatory, infrastructural, and societal fronts.

5. RECOMMENDATIONS

Based on the empirical findings and Lithuania's exemplary transition away from landfill reliance, this article propose several measures Albania can adopt and adapt to accelerate its circular economy transformation:

Strengthen Regulatory Framework. Lithuania's success has hinged on a strong legal framework aligned with EU directives banning the landfilling of untreated and biodegradable waste, while gradually increasing landfill taxes (European Environment Agency, 2025b) Albania should follow suit by enforcing bans on recyclable and biodegradable landfilling and introducing economic disincentives such as progressive landfill taxes(European Commission, 2023).Mandatory waste separation at source and well-structured extended producer responsibility (EPR) schemes effectively implemented in Lithuania can also be replicated in Albania to boost recovery rates and producer accountability (European Environment Agency, 2025b)

Infrastructure Development. Lithuania's progress relied on investments in separate collection systems, waste sorting centers, composting units, and waste-to-energy facilities.(European Environment Agency, 2025b) Albania should similarly develop regional infrastructure for recycling and organics treatment while considering incineration only for residuals. EU cohesion funds or public-private partnerships could support this transition. Importantly, as Lithuania closed or modernized non-compliant landfills, Albania should prioritize upgrading disposal sites with proper environmental controls (European Commission, 2023a)

Institutional and Governance Reforms. Lithuania's centralized oversight and municipal collaboration helped coordinate policy execution. (European Commission, 2023b)Albania could benefit from establishing a national circular economy task force, improving local government capacity for enforcement, and strengthening data collection systems for waste tracking. (European Commission, 2023b). Transparent procurement and performance-based contracts, as seen in Lithuania, would enhance efficiency and reduce corruption (European Commission, 2022)

Economic Incentives. Lithuania's deposit-refund scheme among the most successful in the EU achieved over 90% return rates for beverage containers (TOMRA Systems ASA, 2020). Albania should introduce a similar system, along with "pay-as-you-throw" schemes for households. Redirecting subsidies from landfilling toward recycling enterprises and offering incentives for circular product design can help shift the market in favor of sustainability (Organisation for Economic Co-operation and Development (OECD), 2024)

Public Awareness and Behavior Change. Lithuania achieved high public participation through national awareness campaigns, school programs, and NGO partnerships (European Commission, 2023b). Albania should launch similar outreach efforts to promote recycling, composting, and responsible consumption. Clear labeling, accessible infrastructure, and education about the economic and environmental benefits of proper sorting are essential. Lithuania's integration of informal waste pickers into formal systems also offers a socially inclusive pathway for Albania (European Commission, 2023b).

Set Measurable Milestones. Lithuania's landfill rate fell from ~60% to <8% in under a decade. Albania could adopt a phased target approach e.g., reduce landfill reliance to 50% by 2027, 30% by 2030 aligned with EU accession milestones. Regular progress reviews and benchmarking against Lithuania and other EU states would help maintain accountability.

6. CONCLUSIONS

This study provided a comprehensive assessment of municipal waste management trajectories in Albania and Lithuania, yielding both methodological and policy-relevant contributions. Methodologically, it was demonstrated an integrated approach that combined clustering, time-series decomposition, regression analysis, and Monte Carlo simulation to analyze waste management performance. This approach allowed us to characterize the current state and dynamics of waste disposal in a comparative context and to quantify how changes in key factors could affect future outcomes. The empirical insights from this analysis are clear: Albania remains in an early stage of the waste management transition, heavily dependent on landfilling, whereas Lithuania has effectively executed a transition to modern, low-landfill waste practices. It was found that over 2014–2023 Albania's landfill rate showed little improvement, in contrast to Lithuania's dramatic decline in landfill usage to single-digit percentages. The cluster analysis underscored this gap, grouping Albania with high-landfill observations and Lithuania with low-landfill ones, and the STL decomposition further highlighted the lack of a downward trend in Albania against the strong negative trend in Lithuania. Our regression results reinforced the importance of waste recovery efforts increased recycling and energy recovery correlate with significantly lower landfill rates and indicated that favorable socioeconomic conditions and post-2019 policy measures are associated with reduced landfilling (though the latter effects need stronger data to confirm). The Monte Carlo scenario projections suggested that even a moderate improvement in Albania's recycling rate (along with ongoing urbanization) could meaningfully lower its landfill reliance, although achieving EU-conforming levels would require far more aggressive improvements. In terms of policy implications, the study confirms that aligning with EU waste management targets will be a considerable challenge for Albania, but not an insurmountable one. The experience of Lithuania offers a blueprint of robust policy enforcement, infrastructure investment, and public engagement that yields rapid progress in waste diversion. Albania can leverage these lessons, but must tailor them to its context and urgently step up the pace of implementation. The recommendations outlined spanning regulatory reforms, infrastructure upgrades, incentive mechanisms, and public education provide a starting point for actionable steps. Ultimately, transitioning from a linear waste model (collect–landfill) to a circular economy model (reduce–recycle–recover) is a long-term endeavor that requires political will, societal support, and sustained resource allocation. This study contributes evidence that such a transition is necessary and highlights which leverage points can have the greatest impact. For future research, a fruitful direction would be to expand the comparative scope: examining a larger set of countries (including those in the Western Balkans and new EU member states) could validate and generalize the patterns identified here. Additionally, integrating qualitative analyses of policy implementation or case studies of specific interventions (such as the rollout of recycling programs) would complement the quantitative findings and provide deeper insight into causality. As data availability improves, researchers could also employ dynamic modeling or system dynamics approaches to simulate the evolution of waste systems under various policy scenarios (Xu et al., 2020). Finally, investigating the economic and environmental co-benefits of circular economy measures such as job creation in the recycling sector or reductions in greenhouse gas emissions from landfills would help build a more holistic case for change (European Commission, 2020). In conclusion, this study has highlighted a significant disparity in waste management outcomes between Albania and Lithuania, reflecting different stages of progress toward sustainable waste management. By clearly documenting the trends and statistically linking them to key factors, it was provided a diagnostic of where Albania stands and what factors could drive improvement. The path forward for Albania will require concerted efforts on multiple fronts, as discussed, but the Lithuanian success story and our scenario analysis together indicate that meaningful improvements are attainable with the right mix of policies and investments. Bridging the gap to EU standards will be challenging, but it is a crucial component of Albania's broader development and environmental protection goals. The transition to a circular economy, while complex, offers long-term benefits for economic efficiency, public health, and environmental sustainability making it an imperative for policymakers and society alike (European Environment Agency, 2021c).

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BRIDGING THE DIGITAL DIVIDE IN ALBANIAN AGRICULTURE: A UTAUT-BASED STUDY ON FARMERS' ADOPTION OF E-AGRICULTURE TOOLS

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Abstract

This study examines the factors influencing Albanian farmers' adoption of e-agriculture tools using the Unified Theory of Acceptance and Use of Technology (UTAUT) framework. While integrating Information and Communication Technology (ICT) into Albania's agricultural sector promises enhanced productivity, improved market access, and greater sustainability, significant barriers persist, including infrastructure constraints and low digital literacy. To identify critical drivers of e-agriculture adoption, Structural Equation Modeling (SEM), supported by Exploratory Factor Analysis (EFA) and Confirmatory Factor Analysis (CFA), was applied to data collected from 854 farmers across three key agricultural regions. Results reveal that Performance Expectancy, Effort Expectancy, and Social Influence significantly and positively affect farmers' intentions to adopt digital tools, while Facilitating Conditions primarily exert an indirect effect through enhancing perceived utility. The study emphasizes the necessity of targeted digital literacy programs, investments in rural ICT infrastructure, and strengthened institutional support to bridge existing technological gaps. These insights provide actionable guidance for policymakers aiming to foster rural economic growth through effective e-agriculture adoption strategies.

Keywords: E-Agriculture, ICT adoption, UTAUT framework, Structural Equation Modeling, Digital transformation in agriculture

1. INTRODUCTION

Integrating digitalization and Information and Communication Technology (ICT) into Albania's agricultural sector is essential and presents significant opportunities. Agriculture is a fundamental component of the Albanian economy, and digital tools have considerable potential to improve productivity, optimize processes, and promote sustainability. Albania's agricultural sector encounters significant challenges, notably a marked digital divide that adversely impacts rural and low-income areas. This divide obstructs the adoption of innovative technologies crucial for contemporary agricultural practices (Mulliri et al., 2021; Sinaj, 2024; Tomorri et al., 2024) . Information and Communication Technology (ICT) enhances farmers' access to information, facilitating data-driven decision-making in crop management, market access, and resource utilization (Kountios et al., 2023; Shah, 2022). Digital platforms enhance communication within the agri-food supply chain, providing advantages to farmers, food processors, and suppliers. Despite these advantages, the adoption of ICT in Albanian agriculture remains nascent, hindered by inadequate infrastructure, low levels of digital literacy, and insufficient institutional support (Mulliri et al., 2021; Tomorri et al., 2024). The Albanian government has acknowledged digital connectivity's significance and enacted policies to improve digital infrastructure within its overall economic growth strategy (Kumi, 2024; Mitaj et al., 2015). Addressing ICT integration's structural and educational challenges necessitates more than mere technological upgrades. Institutional reforms and educational initiatives are essential for adequately equipping farmers with the skills necessary to utilize these tools (Ibrahimi, 2024; Kumi, 2024). Comprehending farmers' behavioral intentions regarding adopting e-Agriculture tools is essential for addressing these challenges. Despite increasing interest in digital agriculture, there remains a lack of empirical studies exploring technology acceptance using the UTAUT model among Albanian farmers, making this study both timely and contextually significant.

This research utilizes the Unified Theory of Acceptance and Use of Technology (UTAUT) framework proposed by Venkatesh et al., (2003) to examine factors including Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Conditions. The study

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analyzes data from 854 farmers in Tirana, Berat, and Korçë utilizing Structural Equation Modeling (SEM), a practical approach for investigating intricate relationships in adoption research (Byrne et al., 2011) . Comprehending farmers' behavioral intentions regarding adopting e-Agriculture tools is essential for addressing these challenges. The findings emphasize the importance of simplicity, social networks, and infrastructure access while revealing barriers such as mistrust and perceived complexity. Addressing these barriers requires concerted efforts from the public and private sectors to invest in digital infrastructure, training, and support systems. These measures will empower farmers to embrace e-Agriculture tools, driving digital transformation in Albania's agricultural practices and fostering long-term sustainability.

1.1 The Role and Adoption of E-Agriculture in Agriculture

Information and Communication Technology (ICT) significantly transforms agriculture by providing essential advantages, including timely weather forecasts, market pricing, and optimal crop management methods, which are crucial for maximizing yields (Gangopadhyay et al., 2019). Digital platforms provide access to financial services, allowing farmers to invest in new equipment and sustainable methods (Dlamini & Worth, 2019). Nonetheless, many obstacles persist, including inconsistent internet access, inadequate digital literacy, and systemic challenges such as limited farm sizes and low production (Mulliri et al., 2021; Sinaj, 2024).
E-Agriculture means utilizing Information and Communication Technology (ICT) in agriculture and rural development. It seeks to augment agricultural output, increase market access, and promote stakeholder communication to tackle hunger and poverty reduction challenges (Maumbe, 2010). The Internet of Things (IoT) plays a critical role in modern farming. IoT applications facilitate the collection and analysis of real-time data, which can optimize farming operations. Sadiku et al. highlight that IoT technologies allow farmers to monitor and manage their practices more effectively, ultimately supporting business growth and better farm management (Sadiku et al., 2021). As technologies improve and become more accessible, farmers can leverage precision agriculture techniques that rely on data analytics and Big Data to make informed decisions about crop management and resource utilization. This trend is evident in regions such as East Kazakhstan, where precision farming is anticipated to enhance agricultural productivity through meticulous data analysis (Тогузова et al., 2023).
Integrated ICT frameworks, as proposed by Ireri et al., are pivotal in improving agricultural productivity among smallholder farmers. The authors outline that farmers face challenges related to accessing critical information that could enhance their practices, such as insights on soil and pest management (IRERI et al., 2022). The introduction of e-agriculture frameworks specifically tailored for rural environments can bridge gaps between research communities and practitioners, thereby improving overall productivity and agricultural sustainability (IRERI et al., 2022). Furthermore, Singh et al., (2015) emphasize that effective utilization of ICTs can significantly enhance the communication processes among stakeholders in the agricultural production system.
The impact of robotics and automation on farming cannot be overlooked. The development of agricultural robotics is transforming traditional farming, enabling autonomous operations for tasks such as weed control and harvesting. These technologies reduce the reliance on manual labor and shift the focus towards automated processes, which not only saves time but also increases efficiency (Shamshiri et al., 2018). Moreover, the application of big data and AI technologies in agriculture fosters innovative information management strategies that can revolutionize farming practices, enhance crop yields, and ultimately contribute to sustainable agricultural development (Li & Wang, 2024).
The emergence of mobile technologies further supports the accessibility of agricultural information. As reported by Pongnumkul et al., (2015) smartphones equipped with various sensors provide a practical solution for farmers to manage their operations effectively. These mobile applications can assist in various farming tasks, including monitoring soil health and irrigation needs, thereby improving overall farm productivity.
Sustainable agricultural practices are also promoted through e-agriculture initiatives. The focus on reducing chemical inputs, as explored by Silva et al., indicates that eco-friendly technologies can promote the effective use of natural resources and align agricultural practices with environmental sustainability goals (Silva et al., 2020). Additionally, the development of comprehensive frameworks for the use of technology in agriculture, as described by authors like Matyja and Rajchelt-Zublewicz, (2018) supports sustainable practices that are both profitable and environmentally sound.
The significance and implementation of e-Agriculture in Albania are increasingly acknowledged as essential for improving agricultural production and sustainability, especially within the nation's transitional economy. E-Agriculture initiatives can enhance information accessibility, improve supply chain coordination, and augment market access for farmers, which is crucial as agriculture constitutes approximately one-fifth of Albania's GDP and employs a substantial segment of the workforce (Mitaj et al., 2015; Zhllima et al., 2022). The use of digital technologies in agriculture is hindered by a digital divide, particularly in rural areas where internet access and technological infrastructure are insufficient (Mulliri et al., 2021; Sinaj, 2024). The potential of e-Agriculture to transform the sector is

highlighted by the need for agricultural cooperatives to foster collaboration and innovation among farmers, thereby addressing challenges stemming from fragmented land holdings and outdated practices (Imami et al., 2021; Vajjhala & Thandekkattu, 2017). Albania's quest for economic reforms and European Union membership requires the implementation of e-Agriculture to modernize its agricultural sector and improve competitiveness in domestic and global markets (Liça, 2024; Mitaj et al., 2015).

2. LITERATURE REVIEW

The variables affecting e-Agriculture tool adoption and the hurdles to their widespread use have drawn academic attention. The Unified Theory of Acceptance and Use of Technology (UTAUT) is utilized to understand agricultural technology adoption (Ning, 2023; Patel et al., 2016). This paradigm states that performance expectancy, effort expectancy, social influence, and conducive factors drive technology adoption (Sanders et al., 2022). The UTAUT framework has been used to study e-Agriculture tool adoption, showing that these variables influence farmers' intentions and actions (Junior et al., 2022; Morris & James, 2017). E-Agriculture tool adoption is consistently predicted by perceived utility and convenience of use (Cao & Solangi, 2023; Ndlovu et al., 2022).
Farmers are more inclined to accept these technologies if they feel they are simple to use and will improve their operations. To address this hurdle, farmers may need training and resources on the benefits of e-Agriculture technologies and how to use them (Junior et al., 2022) . Social and behavioral aspects have an essential influence on adopting e-Agriculture instruments. Lack of knowledge, education, and social networks have been recognized as impediments to implementing sustainable agricultural methods, including e-Agriculture technologies (Amjath-Babu et al., 2018) . Farmers may overcome these hurdles by targeted outreach and education efforts, establishing social relationships, and knowledge-sharing (Mandari et al., 2017). Infrastructural impediments to e-Agriculture tool adoption include poor internet connectivity and the availability of digital resources (Junior et al., 2022) . Improving the availability and dependability of rural broadband infrastructure and giving access to digital resources and training may all assist in overcoming these hurdles. Furthermore, cultural barriers, gender inequities, and legislative and regulatory frameworks can impact adopting e-Agriculture tools (Amjath-Babu et al., 2018). Addressing these constraints may necessitate a diverse strategy, such as developing supporting regulations, promoting gender parity, and integrating traditional institutions and social networks (Pratomo, 2023).
The application of the Unified Theory of Acceptance and Use of Technology (UTAUT) model to e-agriculture, smart farming, and digital agriculture has increasingly gained scholarly attention due to its effectiveness in exploring factors influencing farmers' adoption of innovative agricultural technologies. This synthesis critically examines recent contributions utilizing the UTAUT framework, emphasizing the theoretical robustness and practical applicability of this model within these emerging agricultural domains.
The UTAUT model, originally proposed by Venkatesh et al. (2003), identifies four primary constructs—performance expectancy, effort expectancy, social influence, and facilitating conditions—that significantly impact users' behavioral intentions toward new technology adoption. In agricultural contexts, Markovits (2024) emphasizes the importance of understanding Romanian farmers' motivations for technology adoption, highlighting the UTAUT model's effectiveness in capturing nuanced attitudes and barriers influencing digitalization decisions in agriculture.
The Technology Acceptance Model (TAM), proposed by Davis (1989), has also widely influenced technology adoption studies by emphasizing perceived usefulness and ease of use as core determinants of user acceptance. TAM consistently demonstrates predictive accuracy across various technological contexts, including agriculture (Ahmed et al., 2021; Wang et al., 2023). Integrating insights from TAM provides additional theoretical support for UTAUT's constructions, particularly in emphasizing the central roles of performance expectancy and effort expectancy in driving farmers' adoption decisions.
Furthermore, the Technological-Organizational-Environmental (TOE) framework complements UTAUT by offering a comprehensive lens to analyze technology adoption at the organizational and systemic levels. As highlighted by Lian-ying et al. (2024), combining TOE with UTAUT enriches analysis by acknowledging technological compatibility, organizational capabilities, and environmental facilitators and barriers that influence farmers' decisions regarding digital agriculture technologies.
Expanding upon UTAUT's utility, studies by Lian-ying et al. (2024) and Sun et al. (2021) demonstrate its relevance in examining farmers' adoption intentions specifically related to Internet of Things (IoT) technologies, which are critical for improving farm operational efficiency and sustainability. Lian-ying et al. (2024) notably integrate UTAUT with TOE, illustrating a comprehensive analytical approach capturing individual perceptions and broader contextual influences.
Additionally, literature highlights the critical role of external factors, such as financial incentives and technical guidance, in promoting digital technology acceptance among farmers. Gao et al. (2024) underlines the effectiveness of financial instruments, including subsidies and tax incentives, in mitigating farmers' initial economic hesitations, thus positively influencing adoption decisions.
Recent extensions of the UTAUT model have

incorporated supplementary constructs reflective of evolving technological environments and social dynamics within agricultural communities. Ahmed et al. (2021) and Wang et al. (2023) explore the impacts of social networks, collaborative interactions, and community-driven knowledge sharing, demonstrating these factors' substantial roles in shaping farmers' acceptance and diffusion of digital technologies.
Furthermore, Sabbagh and Gutierrez (2022) underscore the pivotal role of effective agricultural extension services in supporting digital transitions, illustrating how targeted extension programs significantly enhance farmers' technological literacy, confidence, and practical adoption rates. Rotz et al. (2019) complement these findings by discussing broader implications of digital agricultural practices, particularly precision agriculture and data-driven methodologies, highlighting their transformative potential across agricultural landscapes.
While frameworks such as the Technology Acceptance Model (TAM) and the Technological-Organizational-Environmental (TOE) model have been widely employed in the literature, this study exclusively utilizes the UTAUT framework. This decision was driven by UTAUT's comprehensive structure, explicitly encompassing Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Conditions, which closely align with the agricultural technology adoption context under study. The questionnaire and subsequent analysis in this research were constructed specifically on these UTAUT constructions, thereby maintaining methodological consistency and clarity.

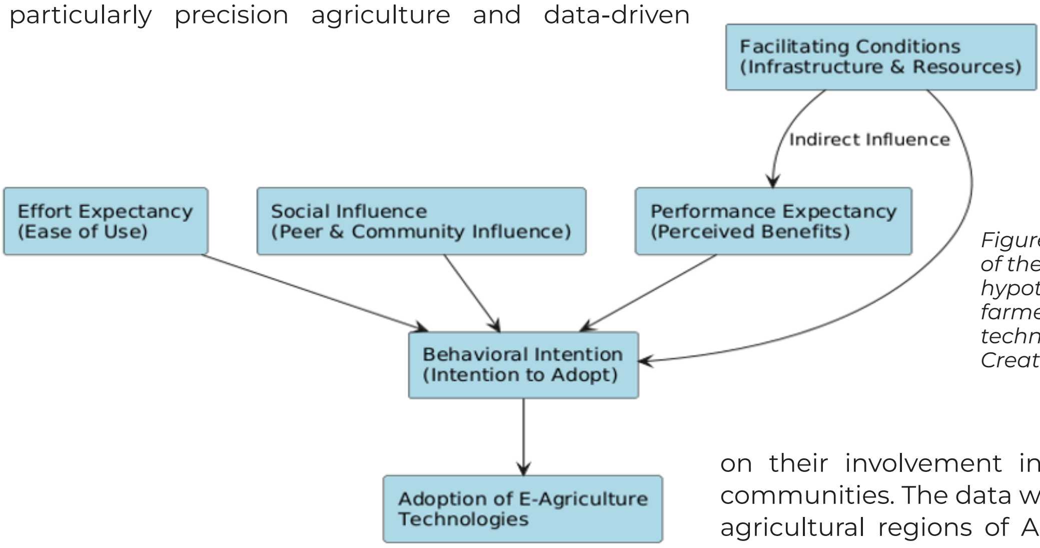

Figure 1. Conceptual representation of the UTAUT constructs and hypothesized relationships influencing farmers' adoption of e-Agriculture technologies in Albania. Source: Created by the authors.

3. METHODOLOGY

Using the Unified Theory of Acceptance and Use of Technology (UTAUT) paradigm, this study investigated the factors influencing Albanian farmers' behavioral intentions to use e-Agriculture instruments. The objectives were to:

1. Determine the factors influencing behavioral intention, such as Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), and Facilitating Conditions (FC).
2. Assess the direct relationships between the UTAUT constructs and Behavioral Intention (BI).
3. Examine the indirect effect of Facilitating Conditions on Behavioral Intention through Performance Expectancy.

The following questions guided the research:

1. What factors significantly influence farmers' intentions to adopt e-Agriculture tools?
2. How do Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Conditions impact Behavioral Intention?
3. Does Facilitating Conditions indirectly affect Behavioral Intention through Performance Expectancy?

3.1 Sampling and data collection

The challenges associated with accessing rural agricultural populations were addressed by employing a non-probabilistic convenience sampling method in the study. Participants were chosen based on their involvement in agricultural networks and communities. The data was collected in three primary agricultural regions of Albania: Tirana District, Berat District, and Korçë District. The districts are chosen based on the availability of resources, including Internet connectivity and mobile devices, as well as their diverse agricultural practices and degrees of technological exposure. A response rate of 57% was achieved by contacting 1,500 farmers, resulting in 854 valid responses. The sampling method used was non-probabilistic convenience sampling, chosen due to logistical considerations such as ease of access and availability of respondents through local farming communities. While practical, this approach limits the generalizability of findings to all Albanian farmers.

3.2 Instrument design

A structured questionnaire was designed based on the UTAUT framework by Venkatesh et al. (2003), comprising five constructs:

- Performance Expectancy (PE): Perceived benefits of e-Agriculture tools in improving productivity.
- Effort Expectancy (EE): Ease of use of the tools.
- Social Influence (SI): Encouragement from peers, family, and community leaders.
- Facilitating Conditions (FC): Availability of supporting resources.
- Behavioral Intention (BI): Likelihood of adopting e-Agriculture tools.

Each construct was measured using five Likert-scale items, rated from 1 (Strongly Disagree) to 5 (Strongly Agree). The questionnaire was pre-tested for clarity and reliability before distribution.

3.3 Distribution method and data preparation

The questionnaire was disseminated through Google Forms and WhatsApp. Descriptive statistics and data cleansing were implemented through Python preprocessing. R was employed to conduct sophisticated statistical analyses, including confirmatory factor analysis (CFA) and structural equation modeling (SEM), with the assistance of the lavaan package. As for the software tools, python was used for data cleaning and descriptive statistics. R (lavaan and semPlot) for conducting EFA, CFA and SEM in RStudio.

3.4 Analysis steps

Reliability testing using Cronbach's Alpha was employed to evaluate the internal consistency of each construct, with all attaining acceptable levels (□ > 0.7). Cronbach's alpha, a well-established metric for internal consistency dependability, functions as a minimum threshold for test reliability, signifying that ideal essential tau-equivalence is seldom attained. This metric is frequently employed in several domains to evaluate the reliability of measurement instruments, with a threshold of 0.70 or above typically considered acceptable (Cortina, 1993; Lee et al., 2023).
Exploratory Factor Analysis (EFA) was utilized to investigate the latent structure of the dataset, validating the categorization of questionnaire questions within the UTAUT categories. Exploratory Factor Analysis (EFA) is a statistical method employed to reveal the latent structure of a collection of observable data. It frequently functions as an initial phase in Structural Equation Modeling (SEM) to discern latent constructs and guide later confirmatory analyses (Anderson & Gerbing, 1988; Tekin & Polat, 2016).
The CFA confirmed the suitability of the UTAUT model for the data. Confirmatory Factor Analysis (CFA) is utilized in the Unified Theory of Acceptance and Use of Technology (UTAUT) context to validate the factor structure of its core constructs: performance expectancy, effort expectancy, social influence, and facilitating conditions. This process ensures that these latent variables accurately represent the observed data and enhance the integrity of the technology acceptance model (Dönmez-Turan, 2019).
Structural Equation Modeling (SEM) is a robust statistical method employed within the framework of the Unified Theory of Acceptance and Use of Technology (UTAUT) to analyze the interrelations among critical constructs, including performance expectancy, effort expectancy, social influence, and facilitating conditions, thus offering an extensive framework for comprehending technology adoption behaviors (Chao, 2019; Williams et al., 2010). This methodology enables researchers to authenticate the measurement model and investigate the structural links among components, providing insights into how these elements affect consumers' intentions to embrace new technologies (Chao, 2019; Kabra et al., 2017). Structural Equation Modeling evaluated the associations between the UTAUT components and Behavioral Intention. The model evaluated the subsequent hypotheses:

- H1: Performance Expectancy positively influences Behavioral Intention.
- H2: Effort Expectancy positively influences Behavioral Intention.
- H3: Social Influence positively influences Behavioral Intention.
- H4: Facilitating Conditions positively influence Behavioral Intention.
- H5: Facilitating Conditions positively influence Performance Expectancy.

4. RESULTS

This section presents the study's findings through detailed statistical analysis, hypothesis testing, and structured explanations. The results are presented in textual and tabular formats to enhance clarity and coherence. The dataset comprised 854 responses from farmers in Albania's Tirana, Berat, and Korçë districts. Table 1 summarizes key demographic distributions.

Table 1 - Distribution of Gender, Age, Farm Size, Education Level, and Internet Usage Among Farmers in the Study Sample

Variable	Distribution
Gender	90% Male, 10% Female
Age	18-30: 10%, 31-45: 40%, 46-60: 40%, >60: 10%
Farm Size	<1 hectare: 20%, 1-5 hectares: 70%, >5 hectares: 10%
Education Level	Primary: 30%, High School: 50%, University: 20%
Internet Usage	Low: 40%, Moderate: 40%, High: 20%

These demographics align with the agricultural landscape of Albania, where the average farm size is 1.4 hectares, and most farmers are male with moderate to high experience in farming (Tomorri et al., 2024).

Table 2 - Response distributions for all questionnaire items

Statistic	**Min**	**Max**	**Mean**	**Std. Dev**
Performance Expectancy	1	5	4.1	0.6
Effort Expectancy	1	5	3.8	0.7
Social Influence	1	5	3.5	0.8
Facilitating Conditions	1	5	3.9	0.6
Behavioral Intention	1	5	4.2	0.5

The mean scores for Performance Expectancy (4.1) and Behavioral Intention (4.2) indicate favorable perceptions of e-Agriculture tools and a willingness to adopt them. Social Influence (3.5) shows moderate encouragement from peers and experts, suggesting room for more assertive advocacy. These findings confirm the robustness of the questionnaire and its suitability for further analysis.

Reliability testing assesses the internal consistency of constructs (e.g., Performance Expectancy, Effort Expectancy) to ensure that the items within each construct measure the same underlying concept. The most common metric used is Cronbach's Alpha, which ranges from 0 to 1:

- ≥0.7: Acceptable reliability.
- ≥0.8: Good reliability.
- ≥0.9: Excellent reliability.

Cronbach's Alpha was calculated to assess the internal consistency of the constructs. As shown in Table 2, all constructs demonstrated excellent reliability, with values exceeding the threshold of 0.7.

Table 3 - Reliability Analysis of UTAUT Constructs Using Cronbach's Alpha

Construct	Cronbach's Alpha	Interpretation
Performance Expectancy (PE)	0.917	Excellent internal consistency
Effort Expectancy (EE)	0.891	Excellent internal consistency
Social Influence (SI)	0.919	Excellent internal consistency
Facilitating Conditions (FC)	0.922	Excellent internal consistency
Behavioral Intention (BI)	0.938	Excellent internal consistency
Overall Reliability	0.970	Excellent internal consistency

EFA was conducted to identify the latent structure of the dataset and determine how the observed items cluster into latent constructs. The objective was to validate the hypothesized constructs derived from the UTAUT framework: Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), Facilitating Conditions (FC), and Behavioral Intention (BI). The EFA extracted five distinct factors, with the following item loadings across latent factors:

Table 4 - Factor Loadings from Exploratory Factor Analysis (EFA) of UTAUT Constructs

Item	ML5	ML1 (PE)	ML2	ML4	ML3 (SI)
PE1		0.65	0.37		
PE2		0.65	0.38		
PE3		0.69	0.34		
PE4		0.69	0.35		
PE5		0.68	0.35		
EE1	0.52	0.50	0.30		
EE2	0.50	0.54	0.29		
EE3	0.50	0.53	0.29		
EE4	0.49	0.50	0.36		
EE5	0.51	0.54	0.29		
SI1					0.74
SI2					0.76
SI3					0.74
SI4					0.77
SI5					0.73
FC1	0.75				
FC2	0.76				
FC3	0.76				
FC4	0.74				
FC5	0.77				
BI1	0.53	0.56	0.50		
BI2	0.52	0.55	0.52		
BI3	0.52	0.53	0.52		

Note: The table shows how each survey item aligns with specific factors based on the UTAUT framework. A higher loading value (typically above 0.7) indicates a strong relationship between the item and the underlying construct. For example, PE1–PE5 load strongly on ML1, which represents Performance Expectancy. Cross-loadings (moderate values in multiple factors) suggest that an item may relate to more than one construct, which is expected in behavioral research. Items BI1–BI3 have moderate loadings on multiple factors, reflecting their shared variance with both effort and performance perceptions.

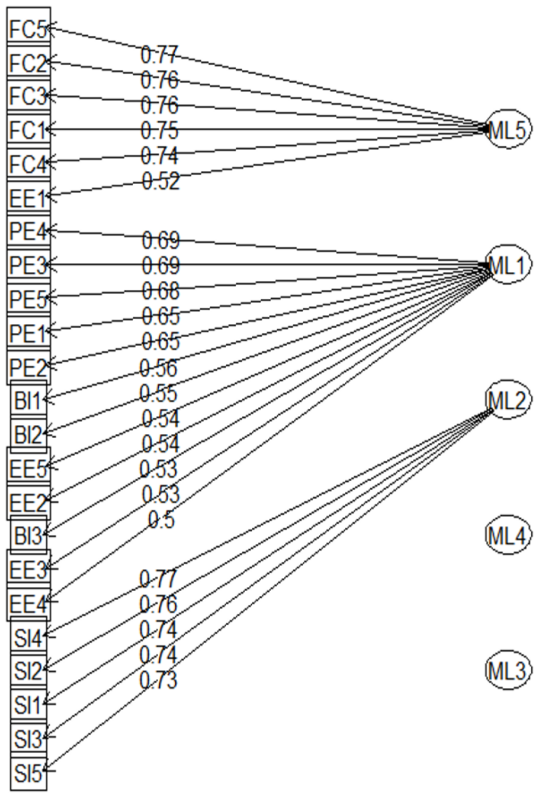

Figure 2. Factor Structure of UTAUT Constructs in E-Agriculture Adoption – Results from Exploratory Factor Analysis (EFA). Source: Authors' own elaboration.

Five factors were extracted, and their loadings align with the hypothesized constructs in the UTAUT model:
Factor 1 (ML1): Performance Expectancy (PE)
Factor 2 (ML2): Effort Expectancy (EE)
Factor 3 (ML3): Social Influence (SI)
Factor 4 (ML4): Residual or cross-loadings
Factor 5 (ML5): Facilitating Conditions (FC)
Items loaded most strongly onto their expected factors, supporting the hypothesized constructs:
PE1–PE5 loaded significantly onto **ML1 (Performance Expectancy).**
EE1–EE5 loaded onto **ML2 (Effort Expectancy)**, but some cross-loadings with ML5 (Facilitating Conditions) were observed.
SI1–SI5 loaded strongly onto **ML3 (Social Influence).**
FC1–FC5 loaded onto **ML5 (Facilitating Conditions).**
BI1–BI3 showed notable loadings across **ML1, ML5,** and **ML2**, indicating some shared variance.
The retrieved factors jointly accounted for a substantial percentage of the variance in the data, validating the validity of the factor structure. Certain cross-loadings (e.g., BI1–BI3 on ML1 and ML2) indicate shared variation between variables such as Behavioral Intention (BI) and Performance Expectancy (PE). The EFA findings corroborate the proposed factor structure of the UTAUT model, with five different components accounting for most of the variance. Minor cross-loadings and residual factors indicate possible overlaps among Facilitating Conditions, Effort Expectancy, and Behavioral Intention, which can be elucidated in future Confirmatory Factor Analysis (CFA).
Fit indices validate a perfect match of the data to the expected model. The model fits the data well since all RMSEA, CFI, TLI, and SRMR thresholds surpass the advised values. Strong correlations between all items with high and significant standardized loadings (> 0.7) about their respective latent components are verified. The observed indicators of the hidden variables—performance expectation, effort expectation, and social influence—show good representation. Significant differences between constructions (e.g., PE ↔ EE, BI ↔ FC) confirm the theoretical links suggested in the UTAUT model. Low residual variances mean that the model explains most of the variance noted. This study shows that for structural modeling or additional hypothesis testing, the assessed constructs of the questionnaire are valid and dependable.

Table 5 - Model Fit Indices for Confirmatory Factor Analysis (CFA) of UTAUT Constructs

Fit Index	Value	Threshold	Interpretation
Chi-Square Test (p-value)	192.491 (p = 0.901)	p > 0.05	The model fits the data well
RMSEA (Root Mean Square Error)	0.000	< 0.08	Excellent fit
CFI (Comparative Fit Index)	1.000	> 0.90	Perfect fit
TLI (Tucker-Lewis Index)	1.002	> 0.90	Perfect fit
SRMR (Standardized Residual)	0.012	< 0.08	Excellent fit

Note: The table presents standard model fit indices used in CFA. Values close to or above the thresholds indicate a good model fit. For example, CFI and TLI values above 0.90 and RMSEA and SRMR values below 0.08 suggest the model accurately represents the data structure.

Table 6 - Standardized Factor Loadings from Confirmatory Factor Analysis (CFA) of UTAUT Constructs

Item	Factor	Standardized Loading	Significance (p-value)
PE1	PE	0.835	< 0.001
PE2	PE	0.821	< 0.001
PE3	PE	0.830	< 0.001
PE4	PE	0.832	< 0.001
PE5	PE	0.832	< 0.001
EE1	EE	0.783	< 0.001
EE2	EE	0.785	< 0.001
EE3	EE	0.785	< 0.001
EE4	EE	0.788	< 0.001
EE5	EE	0.794	< 0.001
SI1	SI	0.835	< 0.001
SI2	SI	0.840	< 0.001
SI3	SI	0.823	< 0.001
SI4	SI	0.838	< 0.001
SI5	SI	0.830	< 0.001
FC1	FC	0.844	< 0.001
FC2	FC	0.840	< 0.001
FC3	FC	0.841	< 0.001
FC4	FC	0.826	< 0.001
FC5	FC	0.838	< 0.001
BI1	BI	0.915	< 0.001
BI2	BI	0.917	< 0.001
BI3	BI	0.910	< 0.001

Note: Factor loadings represent the strength and clarity of each item's relationship with the underlying construct, with values above 0.7 indicating strong construct validity.

The structural model is based on the following hypotheses:

- **H1:** Performance Expectancy (PE) → Behavioral Intention (BI).
- **H2:** Effort Expectancy (EE) → Behavioral Intention (BI).
- **H3:** Social Influence (SI) → Behavioral Intention (BI).
- **H4:** Facilitating Conditions (FC) → Behavioral Intention (BI).
- **H5:** Facilitating Conditions (FC) → Performance Expectancy (PE).

Diagram:

- **Latent Variables:**
  - PE, EE, SI, FC, BI.
- **Direct Relationships:**
  - PE → BI, EE → BI, SI → BI, FC → BI.
- **Mediated Relationship:**
  - FC → PE → BI.

The SEM model fits the data well, as indicated by acceptable fit indices (CFI, TLI > 0.90; RMSEA = 0.051; SRMR < 0.08). The significant chi-square statistic reflects sample size sensitivity, familiar in SEM with larger datasets.

Table 7 - Model Fit Indices for Structural Equation Modeling (SEM) of UTAUT Constructs

Fit Index	Value	Threshold	Interpretation
Chi-Square Test (p-value)	717.566	p < 0.05	The model fits the data moderately well.
RMSEA (Root Mean Square Error)	0.051	<0.08	Acceptable fit.
CFI (Comparative Fit Index)	0.973	>0.90	Good fit.
TLI (Tucker-Lewis Index)	0.969	>0.90	Good fit.
SRMR (Standardized Residual)	0.060	<0.08	Acceptable fit.

Note: This table shows how well the structural model fits the observed data. Fit indices such as RMSEA, CFI, TLI, and SRMR meet standard thresholds, indicating an overall good to acceptable model fit. The slightly significant chi-square is common in large samples and does not undermine the model's validity.

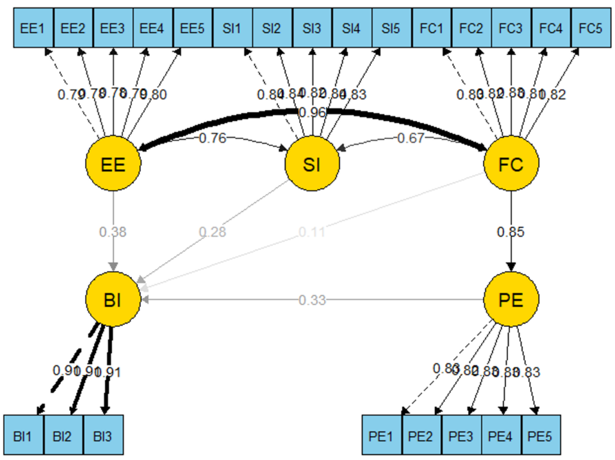

Figure 3. Structural Equation Modeling (SEM) Path Diagram for UTAUT Constructs in E-Agriculture Adoption. Source: Authors' own elaboration.

Path Coefficients:

PE → BI (β = **0.334**): Performance Expectancy is a significant and strong predictor of Behavioral Intention.

EE → BI (β = **0.377**): Effort Expectancy has the most potent effect on Behavioral Intention, indicating the importance of ease of use.

SI → BI (β = 0.284): Social Influence significantly predicts Behavioral Intention but has a moderate effect.

FC → BI (β = 0.109): Facilitating Conditions do not significantly influence Behavioral Intention directly.

FC → PE (β = 0.847): Facilitating Conditions enormously enhances Performance Expectancy, highlighting their indirect effect on Behavioral Intention.

Indirect effect (FC → PE → BI) (β = 0.283): The mediation analysis confirms a significant indirect effect of Facilitating Conditions on Behavioral Intention through Performance Expectancy (β = 0.283, p < 0.001). This indicates that although Facilitating Conditions do not directly predict Behavioral Intention (β = 0.109, p = 0.209), they exert a strong influence indirectly by enhancing users' expectations of performance. This mediated pathway supports the theoretical premise that robust infrastructural and support conditions increase perceived usefulness, which in turn strengthens the intention to adopt e-agriculture tools.

Table 8 - Structural Equation Modeling (SEM) Path Coefficients, Significance Levels, and Hypothesis Testing for UTAUT Constructs in E-Agriculture Adoption

Path	Coefficient (β)	p-value	Hypothesis Supported?
PE → BI	0.334	<0.001	Yes
EE → BI	0.377	<0.001	Yes
SI → BI	0.284	<0.001	Yes
FC → BI	0.109	0.214	No
FC → PE	0.847	<0.001	Yes

Facilitating Conditions (FC) although FC does not directly predict Behavioral Intention, it indirectly drives Behavioral Intention by substantially enhancing Performance Expectancy (PE). For Effort Expectancy (EE) the adoption intentions are most significantly influenced by the perception of convenience. In the case of Social Influence (SI) behavioral intention is moderately influenced by community and peer recommendations. For Performance Expectancy (PE) perceived productivity improvements significantly influence adoption intentions. Behavioral intention is significantly influenced by performance expectancy (PE). PE suggests that users are more likely to employ tools when they perceive clear benefits, such as increased productivity. Effort Expectancy (EE) is the strongest predictor, which suggests that barriers to adoption are substantially reduced by simplicity and ease of use. Social Influence (SI) is a moderate predictor that underscores the significance of peer recommendations and social acceptability in promoting tool adoption. Facilitating Conditions (FC): Although FC does not directly affect BI, its indirect effect through PE underscores its role in creating the necessary conditions for adoption.

Usability Promotes Adoption. When users perceive technologies as straightforward and easy to master, they experience reduced intimidation and are more willing to engage with them. A farmer who believes, "This application necessitates only a few clicks to monitor my crops" will be encouraged to utilize it. Davis (1989), in the Technology Acceptance Model (TAM), highlighted that usability is a crucial determinant in facilitating technology adoption. Social influence generates motivation. Farmers are frequently influenced by social standards or encouragement from peers, family, or community leaders. Individuals are more inclined to adopt instruments when those nearby are utilizing them. A farmer who hears, "My fellow farmers and experts endorse this tool," may be inclined to utilize it. Venkatesh et al. (2003) The Unified Theory of Acceptance and Use of Technology (UTAUT) established that social influence is a significant factor in cohesive communities. Farmers feel empowered to utilize technology when they have access to essential resources such as smartphones, internet connectivity, or training. A farmer with dependable internet connectivity is more inclined to utilize e-Agriculture equipment without concerns regarding disruptions.

Hypothesis were tested. H1: Performance Expectancy (PE) positively affects farmers' Behavioral Intention (BI) to adopt e-Agriculture tools. The hypothesis was supported. Performance Expectancy significantly and positively influences Behavioral Intention ($\beta = 0.504$, $p < 0.001$). This indicates that farmers are more likely to adopt e-Agriculture tools if they perceive them as beneficial in improving productivity. Practical implications include emphasizing productivity benefits through evidence and success stories, building trust, and addressing skepticism. These findings align with Venkatesh et al. (2003), who highlight the importance of perceived usefulness in driving technology adoption.

H2: Effort Expectancy (EE) positively affects Behavioral Intention (BI). H2 was supported. Effort Expectancy is the strongest predictor of Behavioral Intention ($\beta = 0.591$, $p < 0.001$). Simplicity and ease of use are critical drivers for adoption. Farmers are more likely to adopt intuitive tools requiring minimal learning effort. Developers should prioritize user-friendly interfaces and provide accessible training programs to lower perceived barriers. This result supports (Davis, 1989), who emphasized that ease of use is a key determinant of technology adoption in the Technology Acceptance Model (TAM).

H3: Social Influence (SI) positively affects Behavioral Intention (BI). H3 was supported. Social Influence has a moderate but significant effect on Behavioral Intention ($\beta = 0.310$, $p < 0.001$). Farmers are encouraged by their peers, family, and community leaders to adopt e-Agriculture tools. Leveraging social networks and organizing community-driven demonstrations can enhance adoption rates, as peer endorsement is influential in tightly knit farming communities. This finding is consistent with Venkatesh et al., (2003), who demonstrated that social influence plays a significant role in technology adoption, particularly in collectivist societies. Hypothesis 4: Facilitating Conditions (FC) → Behavioral Intention (BI). H4 was not supported. Facilitating Conditions do not significantly affect Behavioral Intention ($\beta = 0.137$, $p = 0.214$). This suggests that while access to resources like smartphones, internet, and technical support is necessary, it alone does not directly motivate adoption. However, facilitating conditions remain essential in a broader strategy, including addressing behavioral and educational barriers.

Hypothesis 5: Correlations Between Constructs. H5 was supported. Facilitating Conditions strongly influence Performance Expectancy ($\beta = 0.706$, $p < 0.001$). Farmers with access to the required infrastructure are more likely to perceive these tools as effective. This highlights the importance of providing resources to bolster confidence in the tools' productivity.

5. LIMITATIONS AND FUTURE RESEARCH

Several limitations merit mention. First, the convenience sampling strategy limits generalizability; farmers who participated may have higher initial digital literacy levels than the broader rural farming population. Second, the cross-sectional nature of this study constrains causal inference, highlighting the value of future longitudinal or experimental designs.

Additionally, this study did not examine moderating factors like age, gender, or farm size, which could offer deeper insights into varying adoption dynamics within different subgroups of farmers.

Future research should employ mixed methods approaches, including qualitative interviews to capture deeper insights from farmers who resist digital adoption. Furthermore, longitudinal studies could better establish causal relationships between UTAUT constructs and actual technology usage behaviors.

6. DISCUSSIONS

This study examined Albanian farmers' use of e-agriculture tools through the lens of the Unified Theory of Acceptance and Use of Technology (UTAUT), evaluating the effects of Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating

Conditions on their behavioral intention. The findings revealed that Effort Expectancy emerged as the strongest predictor of Behavioral Intention, followed by Performance Expectancy and Social Influence. Facilitating Conditions, while not directly influencing Behavioral Intention, significantly enhanced Performance Expectancy, indicating an indirect role in shaping farmers' intentions.

These findings are consistent with previous studies utilizing UTAUT in agricultural contexts, particularly in developing countries, where ease of use and perceived usefulness are critical determinants of technology acceptance. The significance of Effort Expectancy underscores the importance of intuitive and accessible interfaces, along with localized instructions and hands-on guidance. Farmers are more likely to engage with digital tools when they perceive them as simple to learn and compatible with their existing practices.

Social Influence also plays a meaningful role in shaping farmers' attitudes, confirming that encouragement from peers, family members, and community leaders contributes to adoption decisions. This highlights the relevance of leveraging social networks, farmer associations, and community demonstration programs to build trust in e-agriculture solutions.

While Facilitating Conditions did not have a direct effect on Behavioral Intention, their strong influence on Performance Expectancy suggests that infrastructure support—such as access to smartphones, internet, and technical assistance—still plays an important enabling role. However, infrastructure alone is insufficient; its value must be clearly connected to perceived productivity and concrete outcomes. Thus, promoting awareness about the tangible benefits of e-agriculture is essential to maximize the impact of infrastructural investments.

The study contributes to the literature by contextualizing UTAUT constructs in a transitional agricultural economy and provides new insights on how indirect relationships between constructs (such as FC → PE → BI) manifest in rural settings. These findings emphasize that technology adoption is not only a matter of access but also of perception, usability, and social reinforcement.study constrains causal inference, highlighting the value of future longitudinal or experimental designs.

Additionally, this study did not examine moderating factors like age, gender, or farm size, which could offer deeper insights into varying adoption dynamics within different subgroups of farmers.

Future research should employ mixed methods approaches, including qualitative interviews to capture deeper insights from farmers who resist digital adoption. Furthermore, longitudinal studies could better establish causal relationships between UTAUT constructs and actual technology usage behaviors.

7. CONCLUSIONS

This research offers a comprehensive view of the factors influencing Albanian farmers' behavioral intention to adopt e-agriculture tools. By applying the UTAUT framework, the study confirms the critical roles of usability, perceived productivity gains, and social encouragement in shaping adoption decisions. While Facilitating Conditions were not a direct determinant of Behavioral Intention, their significant effect on Performance Expectancy illustrates the layered nature of influence in digital adoption processes.

The results point to the need for coordinated efforts between policymakers, technology developers, and agricultural institutions. Improving rural digital infrastructure must be accompanied by strategies that enhance farmers' digital literacy, deliver ongoing technical support, and ensure that tools are designed with the end user in mind. Furthermore, effective communication about the benefits of these technologies—such as increased yields, streamlined operations, and improved market access—can strengthen Performance Expectancy and foster adoption.

This study contributes practical recommendations that align with Albania's broader digital and rural development strategies, including the national Digital Agenda. By addressing both behavioral and infrastructural barriers, the integration of e-agriculture tools can accelerate, supporting greater sustainability, productivity, and resilience in Albanian agriculture.

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SENTIMENT TRENDS ACROSS AGILE AND DIGITAL TRANSFORMATION TOPICS IN REDDIT DISCUSSIONS

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Abstract

Sentiment knowledge in Agile practice and Digital Transformation conversations is important in establishing industry sentiments, issues of adoption, and emerging trends. This study extends previous studies by bridging topic modeling and sentiment analysis in examining sentiment variations between various topics on Agile. Using Latent Dirichlet Allocation (LDA), we analyzed 3,777 Reddit threads and identified salient topics of discussion including Agile approaches, web sites, cognitive challenges, project management, and business uses. Sentiment scores were assigned using VADER to measure the emotional note associated with each topic.The analysis indicates that topics such as cognition, education, and training are likely to have extremely positive sentiment, while software performance, project issues, and market trends are likely to have negative or mixed sentiments. These findings provide us with insightful views into how different aspects of Agile and Digital Transformation are perceived in online discussions. The results have applied value: trainers and practitioners in Agile can focus on reenforcing positively embraced areas while solving the issues revealed during critical conversations. We recommend incorporating targeted training and strategy reforms based on sentiment trends. This work demonstrates the usefulness of applying topic modeling and sentiment analysis for revealing underlying community opinions, creating a soundset toolset for mapping facilitators and inhibitors of Agile adoption.

Keywords: Agile Methodology, Digital Transformation, Sentiment Analysis, Topic Modeling, Natural Language Processing (NLP), Reddit Discussions.

INTRODUCTION

In today's fast-paced and dynamic technology landscape, organizations are increasingly looking towards Agile approaches and Digital Transformation paradigms to stay competitive, responsive, and innovative. Developed initially in software development, Agile approaches have extended far and wide across industries, offering organizations agile and responsive frameworks that facilitate teamwork, incremental refinement, and rapid response to changing marketplace requirements. Concurrently, Digital Transformation initiatives—involving the infusion of digital technologies to completely overhaul processes, cultures, and customer experiences—have become an integral part of strategic organizational growth and survival.

Despite growing adoption, the day-to-day use of Agile frameworks in real-world settings is filled with obstacles, levels of acceptance, and complex perceptions among stakeholders. An understanding of how these practices are perceived by industry experts and broader communities provides valuable insights on adoption enablers, barriers, and emerging trends. Online forums and communities such as Reddit are treasure troves of real-world data that reflect true discourse and diverse opinions about Agile approaches and Digital Transformation. Through such platforms, researchers and practitioners obtain access to narratives generated by communities that are typically indicative of broader organizational opinion.

Previous studies in this area have established the applicability of Natural Language Processing (NLP) methods, i.e., topic modeling and sentiment analysis, to detect thematic trends and affective positions in community forums (Vidgen & Wang, 2009; Ghezzi & Cavallo, 2018; Hidri, Abazi Chaushi, & Tigno, 2024). However, current research has been inclined to emphasize overall sentiment distributions rather than providing an in-depth understanding of how sentiment varies notably by theme. Observing this lacuna, the current study extends earlier work by explicitly linking sentiment polarity to thematic areas identified through topic modeling, thereby providing a more detailed picture of community sentiment towards individual Agile-themed topics.

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Through its integration of topic modeling and sentiment analysis, the current study aims to deliver actionable results that can guide Agile adoption plans, education activities, and organizational decision-making. Specifically, the study responds to the following research questions:
RQ1: What are the top issues emerging in Reddit threads regarding Agile approaches and Digital Transformation?
RQ2: How does sentiment orientation (positive, negative, neutral) vary across these emerged Agile and Digital Transformation issues?
RQ3: What practical insights and recommendations can be derived for Agile professionals based on sentiment fluctuation across specific Agile themes?
The paper is organized in a way that the following section provides an overview of relevant literature, and following that a clear methodology of data collection, preprocessing, sentiment analysis, and topic modeling validation. Next, the results section provides findings that are extensible, the discussion explains these results in detail, and finally, the conclusion includes main contributions, implications, and suggests paths for future research.

LITERATURE REVIEW

Agile practices have emerged as essential to enabling organizations to respond rapidly to dynamic environments, encourage innovation, and achieve team collaboration. Originally constructed for software development, Agile values are now widely applied outside the IT sector, enabling flexibility, continuous delivery, and customer-centric processes (Rigby et al., 2016). Digital Transformation (DT), characterized by the integration of digital technologies into business models, often utilizes Agile practices to enable rapid iteration and adaptive change (Fitzgerald et al., 2014).
Recent studies emphasize the importance of understanding how practitioners and the general public perceive Agile and DT (Saura et al., 2021). Popular social media platforms like Twitter (x) have valuable data to analyze such sentiments (Hidri, Çaushi, Tigno, and Baholli, 2024). Hidri, Çaushi, Tigno, and Baholli (2024) analyzed sentiments in Twitter data through sentiment analysis and found that while most Agile comments were positive, scalability and implementation issues drew critics. Similarly, Spiegler et al. (2022) stated that community-based observations in Reddit forums are describing subtle affective undertones around Agile migrations, including distrust of bureaucratic constraints and loss of control.
Sentiment analysis based on Natural Language Processing (NLP) techniques such as VADER and TextBlob has gained traction more and more in Agile-related research. Both of them have support for automated determination of text that involves sentiment and are especially useful when used alongside social media data (Hutto & Gilbert, 2014; Medhat et al., 2014). Through the application of sentiment analysis, researchers have quantified team morale (Novielli et al., 2018), gauged usability of Agile tools (Koch et al., 2021), and identified the reasons behind dissatisfaction in Agile retrospectives (Mohanani et al., 2021).
To determine themes in large bodies of text, Latent Dirichlet Allocation (LDA) has been utilised extensively in management studies and software engineering (Blei et al., 2003). LDA has been utilised by Bani et al. (2021) to determine emerging priorities in hybrid team structures in Agile project descriptions. Used in conjunction with sentiment analysis, topic modeling allows researchers to follow affective dynamics between themes—a method developed across this research. Hidri and Tigno (2024), in their bibliometric study of Agile Enterprise research, pinpointed a growing scholarly emphasis on Agile scalability, governance, and integration within Digital Transformation. Worth mentioning is that they pointed out a recurring gap for research covering community feeling and public opinion of Agile adoption, which this research directly addresses.
Digital Transformation differs by region. Fata and Myftaraj (2023) discussed the role of digital platforms and ICT in enabling circular economy guidelines in Albania and emphasized the need for cross-disciplinary digital literacy. While not specifically writing on Agile, their article provides regional context to how digital initiatives are accepted and absorbed. Petani et al. (2021) also call for integrating digital transformation guidelines into organizational culture and professional training.

MATERIALS AND METHODS

A. Data Collection and Description

We collected data from Reddit, a vibrant, heterogeneous online community with active discussions on Agile techniques and Digital Transformation. The dataset was 3,777 posts, providing rich, unstructured textual data with diverse community attitudes, perceptions, and experiences.

B. Data Preprocessing

We carried out various preprocessing steps for the textual data using Python and NLP libraries (NLTK, Gensim):

- *Tokenization:* Splitting posts into words.
- *Stop-word Removal:* Removing commonly occurring words and domain-irrelevant terms (e.g., “godzilla,” “batman,” numerical references).
- *Lemmatization:* Lowercasing words to their base form to normalize semantic meaning.
- *Noise Elimination:* Removing URLs, mentions, hashtags, punctuation, and semantically irrelevant special characters to reduce textual noise.

These operations produced a clean, semantically dense dataset most appropriate for topic modeling and sentiment analysis.

C. Sentiment Analysis using VADER

Sentiment analysis was conducted using the VADER (Valence Aware Dictionary and sEntiment Reasoner) algorithm. VADER assigns sentiment polarity based on optimized social media text-specific lexical rules. Compound sentiment score was assigned to each Reddit post, in addition to being labeled as:

- Positive (score > 0.05)
- Negative (score < -0.05)
- Neutral (-0.05 ≤ score ≤ 0.05)

Sentiment categories were then summarized quantitatively to estimate overall community sentiment towards Agile-related issues.

D. Topic Modeling with Latent Dirichlet Allocation (LDA)

Topic modeling was carried out utilizing the Latent Dirichlet Allocation (LDA) algorithm, an Unsupervised machine learning algorithm of widespread use in finding thematic organization in big text data. We ran LDA with 15 topics that we had selected based on preliminary coherence validation (c_v = 0.5482), achieving a balance between thematic coherence and interpretability.

Each Reddit post was annotated with a major topic—the topic with the highest probability score for a particular document.

E. Topic Modeling Validation

For interpretability and relevance of the produced topics, the LDA model had previously been validated using the topic coherence score (c_v metric). After optimization and Gauss preprocessing fine-tuning, the model achieved a coherence score of 0.5482, confirming semantic reliability and consistency of the uncovered topics.

E. Sentiment-Topic Mapping

Following topic assignment and sentiment labeling, we ran a sentiment-topic alignment analysis. We calculated the distribution of sentiment labels (Positive, Negative, Neutral) for every dominant topic, which allowed comparison of the emotional tones in different thematic areas.

G. Visualization and Interpretation

Sentiment by topic was visualized with stacked bar plots, which intuitively revealed sentiment variations within thematic discussions. The visualizations provided a summary of community sentiment trends relating to specific Agile and Digital Transformation topics, allowing for brief and actionable insights.

RESULTS

A. Overall Sentiment Distribution

3,777 Reddit threads relating to Agile methods and Digital Transformation were examined with the assistance of the VADER sentiment analysis tool. The sentiment breakdown Table 1 is as follows:

Table 1 Sentiment Distribution, Generated by the author

Sentiment	Count	Percentage (%)
Positive	2964	78.47
Negative	593	15.70
Neutral	220	5.82

The average sentiment rating was 0.61, indicating a mostly positive sentiment tone in the social media discourse. This is proof of the strength of support and passion for Agile and Digital Transformation practices within the community but with some criticism.

B. Topic Modeling and Dominant Topic Assignment

Topic modeling was performed with Latent Dirichlet Allocation (LDA) and 15 topics. Each post was labeled with its most salient topic—the topic with the highest probability score for a particular document.

Topic Modeling Validation

To ensure topic relevance and interpretability, the performance of the LDA model was earlier measured using the coherence score (c_v metric). After preprocessing optimization and domain-specific noise removal, the coherence score of the final model was 0.5482, confirming the semantic coherence and consistency of the topics. This confirmed setting was reused in the present study to ensure a firm foundation for sentiment linking to thematic structures.

C. Sentiment Variation by Topic

Each sentiment for each post was also compared to its most dominant topic. Mapping this identified certain emotional patterns in different Agile and Digital Transformation topics. Table 2 and Figure 2 presents the sentiment distribution (positive, negative, neutral) by dominant topic.

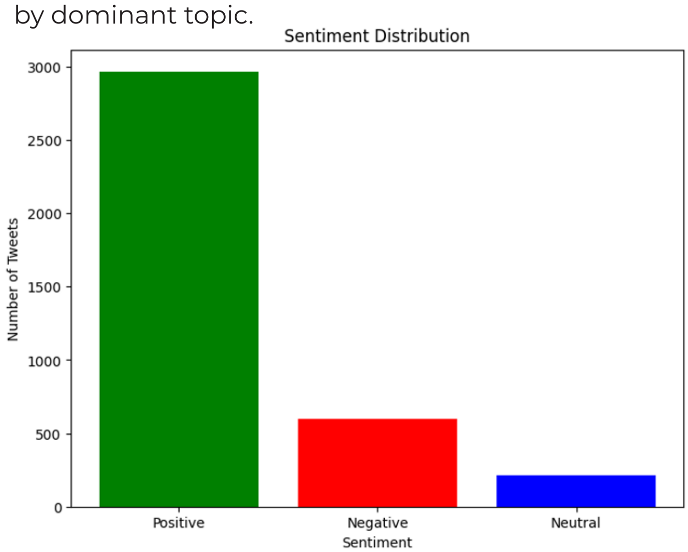

Figure 1 Sentiment Distribution

Main findings are:

Table 2 Topic Sentiment Distribution

Dominant Topic	Positive %	Negative %	Neutral %
0.00	58.16	15.76	26.08
1.00	44.49	55.07	0.44
2.00	84.35	15.65	0.00
3.00	98.87	0.00	1.13
4.00	82.00	18.00	0.00
5.00	96.37	3.11	0.52
6.00	94.51	3.70	1.79
7.00	100.00	0.00	0.00
8.00	48.44	51.56	0.00
9.00	86.77	13.23	0.00
10.00	95.83	4.17	0.00
11.00	93.51	2.60	3.90
12.00	88.44	10.98	0.58
13.00	74.39	25.26	0.35
14.00	83.78	16.22	0.00

Topic 3 (Cognitive and Learning Aspects) had 98.87% positive sentiment, expressing clear appreciation from the community for creativity, mental focus, and intellectual engagement in Agile work.

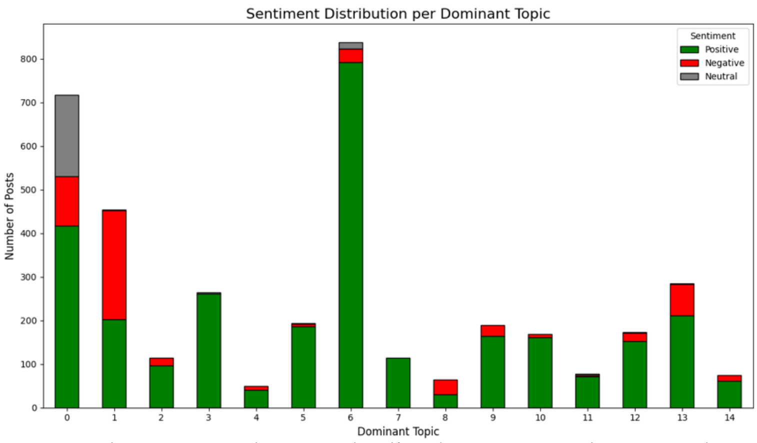

Figure 2 Sentiment Distribution per Dominant Topic

Topic 7 (Hands-on Practice and XP Tools) received 100% positive sentiment, reflecting strong support for Agile tools and hands-on learning frameworks.

Topic 6 (Implementation Refinements) received 94.51% positive sentiment, reflecting positivity about process improvement, changemanagement, and iteration.

Topic 1 (Market and Organizational Critique) received 55.07% negative sentiment, perhaps due to frustration with leadership, practice misalignments, or commercialization of Agile.

Topic 8 (Team Friction or Performance Barriers) recorded a 51.56% negative sentiment, most likely from complaints with group interaction, undefined roles, or misapplication of Agile principles.

Topic 0 (General Agile Discourse) revealed a mixed sentiment profile, at 58.16% positive, 26.08% neutral, and 15.76% negative, typical of exploratory or informative content and not biased opinion.

C. Summary of Key Topic-Level Sentiment Trends shown in Table 3

Table 3 Topic-Level Sentiment

Topic	Description (Keywords)	Positive %	Negative %	Notable Insight
3	Cognitive, creativity, focus	98.87	0.00	Highly favorable discussion on mental engagement in Agile
7	XP, learning tools, practice	100.00	0.00	Total approval for applied Agile frameworks
6	Tiered changes, issue resolution	94.51	3.70	Strong support for process refinement
1	Team, market, organization	44.49	55.07	Criticism of leadership, market pressure, or Agile misuse
8	People, team dynamics, blockers	48.44	51.56	Mixed to negative views, possibly around coordination or resistance

D. Interpretation

These findings highlight that the Reddit community does not receive all Agile and Digital Transformation subjects equally. While topics that touch on training, cognition, and improvement are received with great positivity, those touching on organizational impediments, market skepticism, or implementation failure are received with critical or mixed sentiment.

By linking sentiment distributions to specific topics, the analysis reveals fine-grained details of public opinion about Agile practices. This topic-level resolution is more revealing than aggregated sentiment metrics and enables the identification of salient regions of approval and controversy in Agile discourse.

DISCUSSIONS

This research examined how sentiment varies on some Agile and Digital Transformation issues being discussed on Reddit. From Latent Dirichlet Allocation (LDA), we obtained 15 topics with differing community dialogue ranging from Agile training and cognitive dynamics to market and organizational issues. We assessed the topics using the VADER tool for sentiment analysis and discovered nuanced emotional responses, which largely differed among the topics identified.

We conclude that they propose a largely favorable view towards issues of cognitive benefits, training approaches, and repeated refining processes (e.g., Topics 3, 6, and 7). They all registered over 90% positivity, and Topic 7 (Agile learning tools and XP practices) recorded a complete positivity. These findings suggest strong support among communities of Agile's learning, creativity, and iterative enhancement mechanisms.

Conversely, similar debates around market forces, inner implementation challenges, and software project management issues (e.g., Topics 1 and 8) had significantly more negative emotions. With. more than half of the posts classified as negative in these topics, this indicates. real frustration or criticism in the community about Agile. being used in real-world situations. The existence of mixed emotions in these topics emphasizes the complexity and difficulty that organizations experience in mapping Agile frameworks well with market conditions and internal organizational setups.

Practical Implications and Recommendations

The particular affect variations among Agile-themed topics have particular real-world implications. Practitioners, educators, and decision-makers can utilize these insights in a variety of ways:

Educational Priority: The strongly positive sentiment for cognitive and learning-focused topics shows that organizations should actively work to prioritize Agile training modules, certifications, and cognitive ability building programs. Positive community sentiment suggests that such efforts are sure to be adopted, guaranteeing greater internal buy-in and adoption success.

Focused Interventions in Implementation: Negative attitudes toward market pressure and implementation challenges highlight areas that require additional managerial attention. Companies need to scrutinize Agile implementation in practice in depth, addressing situations of typical friction such as leadership alignment, organizational readiness, and realistic setting, thus actively avoiding negative experiences.

Tailored Communication Strategies: The recognition of difference in sentiment allows organizations to adapt their Agile communications and training strategies. Clearer language on actual marketplace challenges, more open discussion of possible obstacles, and focused preparation for reality in the marketplace can reduce frustration and increase community buy-in and confidence.

Limitations of the Study

In spite of the strength of methodology and analytical precision, a few limitations need to be taken into consideration:

Platform Bias: Users on Reddit may not perfectly reflect the whole professional Agile community. The discussions are naturally biased toward digitally active users, tech-friendly people, and potentially toward particular industries.

Sentiment Analysis Subjectivity: As good as the lexical-based VADER model is, it may not be tapping into advanced expression, sarcasm, or context-specific nuances of natural language. Follow-up work using context-sensitive models like BERT could make such findings more accurate.

Human Interpretation of Topics: Interpretation of topics generated by LDA has some degree of subjectivity, and topic names are interpretative automatically. Varying researchers could classify or define topics very slightly differently.

Future Directions and Recommendations for Further Research

Future research can extend this study in several important ways:

Cross-Platform Comparisons: Comparing the sentiment distributions from Reddit threads to other professional platforms such as LinkedIn or Twitter would even more strongly corroborate or refute these findings, further increasing external generalizability.

Temporal Analysis of Sentiments: Analyzing how sentiment distributions change over time can provide further insights into Agile adoption patterns and maturity levels.

Context-Aware Sentiment Techniques: Employing cutting-edge sentiment analysis techniques with improved comprehension of vague terms may enhance the precision and transparency of sentiment classification, rendering it more applicable.

CONCLUSIONS

This research probed sentiment across unique Agile and Digital Transformation topics being debated among the Reddit community using an integrated approach of topic modeling (LDA) and sentiment analysis (VADER). Our content analysis of 3,777 Reddit posts uncovered interesting differences between community perception according to topic context, highlighting the need for analyzing sentiment not merely in the aggregate but also at a more granular, topic-by-topic level.

The results showed very high cognitive involvement, Agile education, and iterative process improvement themes with strongly positive attitudes. Contrarily, strong negativity was witnessed in themes that addressed market pressure, organizational resistance, and software implementation difficulties. The results show that Agile practices are strongly supported in theory but have practical issues that must be consciously dealt with. In practice, these results offer valuable guidance for Agile practitioners, trainers, and decision-makers to enable targeted strategies that build on strengths and strengthen areas of concern. Organizations can allocate resources better to training and cognition-intensive activities while addressing implementation issues openly and positively.

In summary, this study demonstrates the potential for combining topic modeling with sentiment analysis to learn even more about community sentiment in order to plan even more effective Agile adoption. Future research directions are comparative cross-platform analysis, long-term sentiment studies, and employment of more sophisticated context-sensitive sentiment analysis techniques in order to even more refine these insights.

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Conflict of interests

The authors declare no conflict of interest.

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THE GLOBAL ROLE AND IMPACT OF THE GENERAL DATA PROTECTION REGULATION (GDPR): AN INTERNATIONAL COMPARATIVE APPROACH

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Abstract

The General Data Protection Regulation (GDPR), adopted by the European Union in 2016 and officially implemented since 25 May 2018, has become one of the most powerful digital policy instruments at the global level. Its impact extends beyond the borders of the EU through the extraterritoriality mechanism, obliging international organizations that process data of European citizens to respect its standards. This paper aims to examine the international impact of the GDPR and how countries outside the EU, such as the United States, Brazil, China, but also Albania, have reacted to this regulation.

The study adopts a comparative legal and policy analysis framework, examining the structure, principles, enforcement mechanisms, and institutional capacities of data protection laws in these countries. This methodological approach enables the identification of convergence, divergence, and hybrid models of GDPR influence, providing insights into regulatory diffusion and adaptation processes across diverse legal and political systems.

Through this framework, common elements and essential differences with the GDPR are identified. While countries such as Brazil have adopted similar regulations (LGPD), and some US states have taken unilateral steps towards compliance, other countries, such as China, have created more state-controlled regulations. Albania, as a candidate country for EU membership, has undertaken important legal and institutional reforms to align its legal framework with GDPR standards, including the important role of the Commissioner for the Right to Information and Personal Data Protection.

The paper also addresses the main challenges in the global harmonisation of privacy laws, such as legal complexity, the lack of strong supervisory institutions, and high costs for businesses. In conclusion, the article highlights the potential that the GDPR has to serve as a model towards international standardisation for the protection of personal data, while stressing the need for ongoing dialogue and cooperation between states to ensure a fairer, safer, and more accountable system in the digital age.

Keywords: GDPR, data privacy, European regulations, international laws, data protection, global impact.

1. INTRODUCTION

In the digital age, the protection of personal data has become one of the greatest challenges of democratic societies and modern legal systems. The exponential growth of data processing, through technologies such as artificial intelligence, online platforms, and big data analysis, has increased the need for a strong and comprehensive legal framework to guarantee the privacy of individuals. In this context, the General Data Protection Regulation (GDPR), adopted by the European Union in 2016 and implemented since May 2018, has become a global benchmark for legislation on privacy and the protection of personal data (Voigt & Von dem Bussche, 2021).

The GDPR stands out for its balanced approach between the rights of the individual and the needs of the economic and public sectors to process data. It includes fundamental principles such as transparency, accountability, purpose limitation, and data minimisation, while also imposing strict obligations on data controllers and processors (Kuner et al., 2020). Furthermore, the impact of the GDPR has been felt beyond the borders of the European Union through the principle of extraterritoriality, which requires any entity, regardless of location, that processes data of European citizens to comply with the regulation. Countries outside the EU have been faced with the choice between harmonising their legislation with the GDPR or pursuing alternative data protection paths. Brazil has adopted the General Data Protection Law (LGPD), which is largely inspired by the GDPR, while some US states, such as California, have undertaken unilateral privacy protection initiatives, without a unified national law (Greenleaf, 2021). In contrast, countries such as China have adopted legislation that combines data protection with state security interests, diverging their approach from the European model.

Albania, as a candidate country for membership in the European Union, has also taken important steps to align its legal framework with the EU acquis communautaire. In 2024, the Parliament adopted Law No. 18/2024 “On the Protection of Personal Data”, which aims at full harmonisation with the GDPR and strengthening the role of the Commissioner for the Right to Information and the Protection of Personal Data (Commissioner for Personal Data, 2024). This development represents an important

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step towards consolidating data protection in Albania and integrating European standards into the public administration and the private sector.

This paper aims to analyze the global impact of the GDPR and how this regulation has influenced the development of data protection legislation in various countries, including the USA, Brazil, China, and Albania. Through a comparative and analytical approach, the paper aims to identify global trends, challenges, and potential for international standardization in this vital area of law and technology.

2. LITERATURE REVIEW

2.1 Principles and Purpose of the GDPR

The General Data Protection Regulation (GDPR) is based on seven core principles that represent its legal and ethical foundation. These principles aim to ensure the effective protection of personal data, strengthen the rights of individuals, and increase the accountability of entities that process it (Voigt & Von dem Bussche, 2017; Tikkinen-Piri, Rohunen, & Markkula, 2018).

2.1.1 Lawfulness, fairness, and transparency

This principle requires that personal data should only be processed when there is a lawful basis, such as explicit consent, a contractual agreement, or a legal obligation. Processing should be fair and transparent, informing individuals about the purposes and means of using their data (Voigt & Von dem Bussche, 2017).

2.1.2 Purpose limitation

Data must be collected for specified, explicit, and legitimate purposes and not further processed in a manner incompatible with those purposes (European Parliament, 2016, Art. 5). This helps to avoid the use of data for unauthorized or undisclosed interests of the individual.

2.1.3 Data minimization

Only data that is necessary for the purpose may be collected and processed. This means that data subjects must act with prudence and proportionality (Tikkinen-Piri et al., 2018).

2.1.4 Accuracy

Personal data must be accurate and, where necessary, kept up to date. Data subjects must take steps to correct any inaccurate or outdated data without delay (European Parliament, 2016).

2.1.5 Storage limitation

Personal data should not be stored longer than is necessary for the purposes for which they were collected. After this period, the data should be deleted or anonymized (Voigt & Von dem Bussche, 2017).

2.1.6 Integrity and confidentiality

This principle underlines the need for technical and organizational measures that guarantee the security of personal data, including protection against unauthorized access and accidental loss (Tikkinen-Piri et al., 2018).

2.1.7 Accountability

Institutions that process data should not only respect all of the above principles but should also be able to demonstrate their compliance with them. This includes documentation, auditing, and reporting for transparency to relevant authorities (Voigt & Von dem Bussche, 2017).

2.2 The extraterritoriality of the GDPR: Why does it have a global impact?

One of the most prominent and ambitious elements of the General Data Protection Regulation (GDPR) is the principle of extraterritoriality. This principle stipulates that the GDPR applies not only to organizations located within the European Union (EU), but also to any entity outside the EU that processes personal data of individuals located in the EU, when such data is processed in the context of the provision of goods, services, or monitoring of behavior (European Parliament, 2016, Article 3). This territorial extension has made the regulation have an impact far beyond its geographical borders.

The extraterritoriality of the GDPR has forced many international companies, including those in the US, Asia, and Latin America, to harmonize their privacy and data protection practices with European standards. This has contributed to creating a ripple effect, where national legislations have been reformed to be compatible with EU requirements. For example, California has adopted the California Consumer Privacy Act (CCPA), a law that resembles the GDPR in many respects, while Brazil has introduced the General Data Protection Law (LGPD), which is directly inspired by the principles of the GDPR (Greenleaf, 2018).

This effect is often described as the “Brussels effect”, a term used by Anu Bradford (2020), who argues that due to the size of the EU market and its normative power, European regulations tend to become global standards, even without a formal international agreement. According to her, companies choose to implement the highest standards in order to gain access to the European market and avoid potential sanctions.

Furthermore, the GDPR has created a model that is also applicable to countries that are in the process of integrating with the EU, such as Albania. The new Albanian law on the protection of personal data has been improved in line with GDPR standards, bringing the country closer to the EU legal framework and strengthening public trust in institutions (Personal Data Protection Authority, 2024). In this way, the principle of extraterritoriality not only extends the jurisdiction of the EU but has served as a catalyst for global standardization in the field of digital privacy and citizens’ rights in the information age.

According to the OECD (2023), global data flows are increasingly shaped by regional privacy frameworks like the GDPR, which act as de facto global standards in the absence of a unified international privacy regime.
The second edition of Kuner, Bygrave, and Docksey (2022) provides a comprehensive update on the GDPR's evolving interpretation, particularly in light of landmark cases such as *Schrems II*, which redefined transatlantic data flows.

2.3 The European Union and the Response of Countries Outside the EU

2.3.1 The European Union – The Global Data Protection Model and Standard
The European Union is not only the creator of the General Data Protection Regulation (GDPR), but also the most advanced and rigorous model in the world for the protection of personal data privacy. The GDPR entered into force on 25 May 2018 and aims to harmonizes data protection laws across all EU member states, strengthening citizens' rights and imposing strict responsibilities on organizations that process data (Voigt & Von dem Bussche, 2017).
As referring to the table 1 at Appendix, this regulation has brought a comprehensive approach to the field of privacy, establishing fundamental principles such as transparency, accountability, and informed consent as the basis for any action with personal data. It has also established strong enforcement mechanisms, allowing supervisory authorities in each member state to impose significant fines for violations, which can reach up to 4% of a company's annual global turnover (Kuner, 2020).
Furthermore, the EU has continuously promoted international cooperation in the field of data protection, negotiating data protection agreements with third countries, as well as setting standards for the transfer of personal data outside the EU (Schwartz & Solove, 2019). This has helped the GDPR become a global standard, influencing the laws of other countries and shaping the international discourse on digital privacy.
Accordingly, candidate and aspiring EU membership countries, including Albania, are working to approximate their legislation to the GDPR, considering it a key condition for integration into the union (European Commission, 2023). This shows the great importance of the regulation not only for the EU but also for other regions seeking to improve their personal data protection systems.
Recent studies highlight that GDPR enforcement is becoming more consistent across EU member states and is increasingly influencing international regulatory behavior, especially in countries negotiating data transfer agreements with the EU (Kuner et al., 2023).

2.3.2 USA – A fragmented approach
The United States of America has not yet adopted a general federal law that covers the protection of personal data in a unified manner. American privacy legislation is fragmented, based on different sectors and states (Cate, 2020). However, some states have taken steps to improve the protection of citizens' privacy. The best-known example is that of California, with the California Consumer Privacy Act (CCPA), which entered into force in 2020. Although the CCPA is partly inspired by the GDPR, its main emphasis is on transparency in the collection and processing of data and not necessarily on empowering individuals to control it (Greenleaf, 2018). The CCPA also allows citizens to request the deletion of their data and to know what data has been collected, but it does not hold corporations to the same level of responsibility as the GDPR does.
Solove and Schwartz (2022) emphasize that GDPR has not only reshaped European privacy law but has also become a reference point in American legal scholarship, particularly in discussions about the gaps in U.S. federal data protection frameworks.

2.3.3 Brazil – LGPD Law
Brazil adopted the Lei Geral de Proteção de Dados (LGPD) in 2020, a law that is a direct reflection of the structure and philosophy of the GDPR. The LGPD has brought about a profound transformation in the way organizations in Brazil handle personal data. The law includes clear provisions on consent, transparency, purpose of data use, protection against breaches, and the limitation of international data transfers without adequate protection guarantees (Doneda & Monteiro, 2021). The National Data Protection Authority in Brazil (ANPD) is charged with the implementation and monitoring of this law (Table 1 in the Appendix).

2.3.4 China – PIPL
In 2021, China adopted the Personal Information Protection Law (PIPL), a legal framework that aims to protect individuals' personal data. However, unlike the GDPR and LGPD, the PIPL operates in a much more centralized political context and with stronger state control over data. Although the PIPL contains similar provisions on transparency, purpose limitation, and consent, it also gives Chinese authorities expanded access to personal data, which has raised concerns about individual freedom and human rights (Kemp, 2022).
Zhou and Wang (2021) argue that while China's PIPL mirrors some GDPR principles, such as consent and data minimization, its implementation reflects a fundamentally different approach cantered on state control rather than individual empowerment (Table 1 in the Appendix).

2.3.5 Balkan Countries – Towards EU Approximation
The Western Balkan countries, including Albania, are in the process of approximating their national legislation to the acquis communautaire of the European Union, as part of their preparations for

membership. Albania has recently adopted Law No. 18/2023 “On the Protection of Personal Data”, which follows the previous law of 2008 and brings significant improvements in line with the principles and structure of the GDPR. This law strengthens the rights of data subjects, includes the concept of informed consent, the right to access and rectification, and creates the basis for a clearer role for the Commissioner for the Right to Information and Personal Data Protection (IDP, 2024). In addition to Albania, countries such as North Macedonia, Montenegro, and Serbia have also adopted laws that reflect the impact of the GDPR in reforming national standards of privacy and digital security (Table 1 in the Appendix).

3. METHODOLOGY AND METHODS

3.1 Methodology

This study uses comparative legal analysis to assess the impact of the European Union’s General Data Protection Regulation (GDPR) on data protection frameworks in different jurisdictions. While the comparative approach is implicit throughout the article, this section explicitly describes the methodological basis to enhance transparency and reproducibility. The methodology involves a systematic comparison of laws, regulations, and institutional frameworks in different jurisdictions. The objective is to identify similarities, differences, and legal developments that demonstrate the GDPR’s extraterritorial impact. This approach is based on qualitative legal analysis, grounded in normative and functionalist perspectives.

3.2 Methods

To implement this methodology, the following research methods were applied:
1.Documentary analysis: review of primary legal texts (national data protection laws, EU regulations, international agreements), complemented by secondary sources (academic articles, official reports, legal commentaries). 2.Comparative Legal Mapping: Creation of comparative tables to assess compliance with key GDPR principles (e.g., consent, legal basis, DPO, sanctions). 3.Case Analysis: Selection of representative countries based on defined criteria (regulatory response, legal system, regional impact), allowing for both vertical (EU vs. third countries) and horizontal (third country vs. third country) comparisons.
4.Thematic Coding: Identification of recurring themes, such as GDPR-inspired reforms, compliance mechanisms, and institutional capacity building across different jurisdictions.
By clearly distinguishing methodology (general approach) from methods (specific research tools and phases), the study ensures greater academic rigor and transparency.

3.3 Country Selection Criteria

Countries included in the analysis were selected based on a combination of the following criteria:
• Geopolitical significance (e.g., large economies and regional leaders such as the United States, Japan, and Brazil); • Regulatory response to the GDPR (e.g., countries that have enacted GDPR-inspired legislation or have initiated data adequacy negotiations with the EU, such as the UK, Canada, and South Korea); • Diversity of legal systems, to gain a comparative view of civil law, common law, and hybrid systems; • Availability of legal texts and commentaries in English or other accessible languages.

3.4 Data Sources

The data and legal materials used in this study include:

- Official legal and regulatory documents (e.g., national data protection laws, post-GDPR amendments, government communications);
- EU legal instruments, including the GDPR itself and European Commission adequacy decisions;
- Academic literature, policy documents, and legal commentaries from reputable journals and institutions;
- Reports from international organizations (e.g., OECD, UN, Council of Europe) and data protection authorities (e.g., EDPS, national data protection authorities). All sources were consulted between March and June 2025 to ensure their currency and relevance.

3.5 Analytical Framework

The analysis uses a three-step comparative framework:

- Legal Convergence Assessment: examines the degree of alignment of national laws with key GDPR principles, such as consent, data subject rights, legal basis for processing, and enforcement mechanisms;
- Regulatory Impact Assessment: assesses the practical impact of the GDPR using indicators such as institutional reforms, enforcement measures, and cross-border data flow agreements;
- Regulatory Diffusion Map: identifies the impact of the GDPR as a global regulatory standard, including references to national debates, regional frameworks (e.g., APEC CBPR, African Union Convention), and bilateral agreements. This framework allows for both vertical (EU versus third countries) and horizontal (between third countries) comparisons, highlighting the different degrees of regulatory adaptation and impact.

4. DISCUSSIONS

4.1 Challenges in implementing the GDPR globally

- Costs for small and medium-sized businesses
- Interoperability of national laws
- Lack of strong supervisory authorities in some countries
- Resistance from large economic actors to the restrictions imposed

4.1.1 Costs for small and medium-sized businesses: One of the biggest challenges in implementing the GDPR globally is the high costs faced by small and medium-sized businesses. These organizations often lack the financial and technological resources necessary to meet the detailed requirements of the regulation, including investments in security systems, audits, and staff training. As a result, they may face greater risks of privacy breaches or obstacles to their business development (Greenleaf & Waters, 2018).

4.1.2 Interoperability of national laws: Another important challenge is the lack of interoperability of national laws with the GDPR. Different countries have adopted different data protection rules, which are often inadequate or contradictory to the GDPR. This creates difficulties for companies operating in more than one jurisdiction, requiring complex and often costly solutions to comply with different legal frameworks (Bradford, 2020).

4.1.3 Lack of strong supervisory authorities: Another major problem is the lack of strong supervisory authorities in some countries. While in the European Union there are independent agencies with sufficient powers and resources to monitor the implementation of the GDPR and impose significant fines, in many other countries, the relevant authorities are weak, ineffective, or underfunded, causing the regulations to remain merely on paper without any real implementation (Kuner, 2020).

4.1.4 Resistance from large economic actors: There is also considerable resistance from large economic actors to the restrictions imposed by the GDPR. Global companies that collect and process large amounts of data attempt to minimize the impact of regulations through lobbying, flexible interpretation of the law, and in some cases, challenging the law through legal and political channels. This resistance slows down the improvement and harmonization of global privacy standards (Schwartz & Solove, 2019).

4.2 The Future: Can We Have an International Standard for Privacy?

In the digital age, data protection and privacy are issues of global importance, requiring international coordination to address the various challenges posed by the proliferation of technologies and the interaction between states. In this context, there is a clear trend towards the harmonization and convergence of national and regional regulations on privacy and the protection of personal data.

4.2.1 Key regulations showing a trend towards convergence

• The European Union's GDPR (General Data Protection Regulation) is one of the most rigorous and advanced privacy regulations and has served as a model for many other countries and regions (Voigt & Von dem Bussche, 2017).
• Brazil's LGPD (Lei Geral de Proteção de Dados) is a similar regulation, adapted to the Brazilian and Latin American context (Kuner et al., 2020).
• China's Personal Information Protection Law (PIPL), while differing in legal and policy approaches, also requires strong protection of personal data (Zhou & Wang, 2021).

Although these regulations share many common principles, such as transparency, fairness, and limitations on data processing, political, cultural, and legal differences remain prominent, making it difficult to create a unified global standard.

4.2.2 The role of international standards and global organizations

In this context, international technical standards play an important role in harmonizing practices for privacy management and data security.
• ISO/IEC 27701 is an international standard for privacy information management systems (PIMS). This standard is an extension of ISO/IEC 27001 and provides requirements and guidance for the protection of personal data, helping organizations comply with regulations such as the GDPR (ISO, 2019).
• The ISO/IEC 27000 series (particularly ISO/IEC 27001 and ISO/IEC 27002) focuses on information security management, which is a key component for privacy protection (ISO, 2022).
• In addition to ISO, other organizations and initiatives are promoting international cooperation:
• The OECD has established principles for privacy protection that have influenced national legislation and aim to harmonise policies (OECD, 2013).
• The G20 and the United Nations Human Rights Committee have established cooperation platforms to address global privacy and cybersecurity challenges (UN, 2020).

4.2.3 Challenges to creating an international standard

Despite these initiatives and trends, creating a universal privacy standard has major challenges:
• Cultural and political differences: Approaches to privacy vary from one region to another. For example, some countries value individual privacy more, while others prioritize national security (Greenleaf, 2018).
• Economic advantages and the technology market: International companies often have to deal with different regulations, which can create trade barriers and high compliance costs (Bamberger & Mulligan, 2015).
• Political will and international cooperation: A successful standard requires strong commitment and coordination between countries, which is often lacking due to different political and economic interests (Kuner, 2020).

As awareness and the need for privacy increase globally, the trend towards convergence and harmonization of regulations is evident, relying on international standards such as ISO/IEC 27701. However, achieving a unified global standard requires not only technical and legal compliance but also political will and sincere international cooperation. ISO standards and initiatives by global organizations will play a key role as guides and frameworks for the practical implementation of privacy in a consistent and reliable manner (ISO, 2019; OECD, 2013).

4.3 Legal Divergences and Their Implications

While the comparative results highlight varying levels of GDPR alignment across jurisdictions, the legal divergences observed have concrete implications for international cooperation and cross-border data governance. For instance, countries that have adopted GDPR-like frameworks—such as South Korea or Japan—tend to benefit from streamlined adequacy decisions and enhanced mutual legal assistance, facilitating smoother data transfers with the EU. In contrast, jurisdictions like the United States, which rely on sectoral or less comprehensive data protection models, face ongoing challenges related to fragmented compliance, legal uncertainty for multinational companies, and frequent renegotiations of data transfer mechanisms (e.g., Privacy Shield, now invalidated, followed by the Data Privacy Framework). These legal mismatches can hinder trust, create compliance burdens for international businesses, and complicate regulatory interoperability, particularly in emerging areas like cloud services, AI, and health data. Thus, the differences in legal architecture are not merely technical—they influence the dynamics of global data diplomacy, the negotiation of trade agreements, and the strategic positioning of countries within the evolving global digital order.

4.4 Regional Differences and Concrete Consequences of GDPR Misalignment

The impact of GDPR's extraterritorial influence varies significantly by region, shaped by differing legal traditions, regulatory priorities, and economic interests. Below is a regional breakdown highlighting key challenges and consequences stemming from legal divergences with GDPR standards (Table 2 in the Appendix).

This regional overview illustrates that legal misalignment with GDPR can create barriers to international data flows, increase operational costs for multinational firms, and impede cooperation among regulators. Countries with laws closely mirroring GDPR enjoy strategic advantages such as easier market access to the EU and greater attractiveness to data-driven industries. Conversely, regions with fragmented or nascent frameworks face risks of isolation in the global digital economy.

5. CONCLUSIONS AND RECOMMENDATIONS

1. Global Impact of the GDPR - The GDPR is not just a European Union regulation, but an instrument with extraordinary international impact. It has served as a model for many countries and organizations outside the EU, promoting important principles of privacy protection and individuals' rights in the processing of personal data (Voigt & Von dem Bussche, 2017).

2. Shaping Global Policies - Through its advanced and clear requirements, the GDPR has influenced the shaping of policies and legislation of different countries, pushing towards the harmonization of privacy regulations at the global level. This trend creates opportunities for facilitating international trade and cooperation in the field of technology and digital services (Kuner et al., 2020).

3. Implementation Challenges and Limitations - However, challenges in implementation and interpretation remain great, especially due to cultural, political, and technical differences between countries. Businesses and institutions often face various barriers to achieving compliance with international standards, creating a need for continuous improvement in legal cooperation and harmonisation (Greenleaf, 2018).

4. The EU's Proactive Approach - The European Union has adopted a proactive approach to protecting privacy and setting high standards, providing an example and framework for global actors. This approach has also included initiatives for technological standardisation and the promotion of ISO standards, such as ISO/IEC 27701, which help organisations manage personal data in a secure and trustworthy manner (ISO, 2019).

5. Recommendation for Building a Global System - To achieve a sustainable and effective global system for the protection of personal data, stronger international cooperation is necessary, based on recognised technical standards and sincere political dialogue. Economic advantages and respect for human rights must be balanced fairly, creating a global environment where privacy is respected and ensured equally for all (Bamberger & Mulligan, 2015).

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APPENDIXES:

TABLE 1. A detailed description of the GDPR principles adaptation in the EU and other territories (drawn from the author of this paper, using the literature of this paper).

Country/ Region	Law/Standard Name	Adoption Date	Detailed Description	Key Features/ Challenges	Main References
European Union (EU)	General Data Protection Regulation (GDPR)	May 25, 2018	GDPR is the world's most comprehensive and strict data protection regulation. It harmonizes data protection laws across all EU member states and sets high standards for handling personal data, giving individuals strong control over their data privacy.	High organizational responsibility, fines up to 4% of global turnover, strong enforcement mechanisms, and international cooperation.	Voigt & Von dem Bussche, 2017; Kuner, 2020; Schwartz & Solove, 2019; European Commission, 2023
United States (USA)	California Consumer Privacy Act (CCPA) (leading example)	2020	The USA lacks a unified federal privacy law; privacy laws are sectoral and state-based. California's CCPA is the most prominent law focusing on transparency in data collection and processing, but it does not provide the same level of individual empowerment as GDPR.	Fragmented legal framework, no federal unification, emphasis on transparency, and right to delete data.	Cate, 2020; Greenleaf, 2018
Brazil	General Data Protection Law (LGPD)	2020	LGPD is Brazil's data protection law, directly inspired by GDPR. It sets clear rules on consent, transparency, data usage purpose, protection against breaches, and restrictions on international data transfers. The National Data Protection Authority (ANPD) oversees enforcement.	Significant legal transformation, focus on effective enforcement and monitoring by ANPD.	Doneda & Monteiro, 2021
China	Personal Information Protection Law (PIPL)	2021	PIPL is China's data protection law aimed at protecting individual privacy, but it operates within a highly centralized political environment with strong state control. While similar in transparency and consent, authorities have broad access to personal data, raising concerns.	Strong state control over data, concerns about privacy, and individual rights within China's political context.	Kemp, 2022
Albania	Law No. 18/2023 on Personal Data Protection	2023	Albania's new law aligns with GDPR, improving the previous 2008 law. It strengthens individual rights like informed consent, access, and correction of data, and increases the responsibilities of public and private entities for data protection.	Legal alignment with EU, enhanced transparency and accountability, clear role for Commissioner for Information Rights and Data Protection.	IDP, 2024
Western Balkan Countries (excluding Albania)	National Personal Data Protection Laws	Various years	Western Balkan countries are aligning their legislation with EU standards as part of the European integration process. Their laws reflect GDPR principles and structure, strengthening national privacy and digital security systems, but challenges remain in enforcement and awareness.	Legislative reform is in line with the EU, but challenges in enforcement, administrative capacity, and public awareness.	IDP, 2024

TABLE 2. A regional breakdown highlighting key challenges and consequences stemming from legal divergences with GDPR standards (drawn from the author of this paper, using the literature of this paper).

Region	Key GDPR Misalignments	Concrete Consequences	Examples / Notes
European Union & EEA	Mostly full GDPR compliance	Harmonized data protection, smooth data flows, legal certainty	Member States plus EEA countries, UK post-Brexit with UK-GDPR regime
United States	Sectoral approach, no comprehensive federal law; conflicting state laws (e.g., CCPA)	Complex compliance for companies; repeated negotiations on data transfer frameworks; risk of non-adequacy	Invalidated Privacy Shield, Data Privacy Framework pending
Asia (Japan, South Korea, Singapore)	GDPR-inspired laws, but some gaps (e.g., enforcement intensity, data subject rights scope)	Facilitated adequacy agreements, increased international business trust; still some legal uncertainty	Japan and South Korea have EU adequacy decisions
Latin America	Emerging data protection laws, varying rigor, and enforcement	Legal uncertainty hampers investments; inconsistent cross-border data flows	Brazil's LGPD inspired by GDPR; other countries still developing
Africa	Limited data protection frameworks; draft laws are ongoing	Challenges in attracting foreign investment, fragmented data governance	African Union Convention on Cybersecurity as a regional initiative
Middle East	Varied levels of protection; some GDPR-inspired reforms	Cross-border transfer restrictions; regulatory fragmentation	UAE, Israel, with advanced regimes; others lagging

ARTIFICIAL INTELLIGENCE IN MANAGEMENT: TRANSFORMING BUSINESS PRACTICES AND CORPORATE GOVERNANCE.

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Abstract
Artificial Intelligence (AI) has rapidly emerged as a transformative force in the realm of management. This paper explores how AI reshapes business practices across decision-making, operations, customer engagement, and strategic planning. By integrating AI technologies such as machine learning, natural language processing, and robotic process automation, organizations can significantly improve efficiency, accuracy, and innovation. The study concludes that while AI presents challenges related to ethics, bias, and workforce displacement, its benefits for competitive advantage and long-term sustainability are (IBMTeamData&andAI, 2024) Artificial Intelligence (AI) has emerged as one of the most transformative technologies in recent years, reshaping various aspects of human life, including the business and management sectors. In management, AI is not just a buzzword; it is a powerful tool that drives efficiency, enhances decision-making, and improves customer experiences. This article explores the role of AI in management, its benefits, challenges, and future implications.

Keywords: Artificial Intelligence in management, AI in processes, (AI) on human resource management

INTRODUCTION

Artificial Intelligence (AI) has transitioned from a technological novelty to a vital driver of organizational efficiency and strategic competitiveness. Businesses across all sectors are adopting AI to refine managerial functions, redefine operational procedures, and respond more dynamically to market changes. This paper analyzes how AI is transforming managerial approaches and the broader implications for modern business practices.

(Adam Uzialko, 2024) Perhaps more importantly, it's becoming an increasingly crucial business tool with ramifications across multiple industries (Chui, 2028) Many years ago, in trying to improve manufacturing and production, these improvements were related to the physical world (DiCarlo, 2025). AI in Strategic Decision-Making. One of the primary areas where AI is making an impact is in strategic decision-making. AI technologies, such as machine learning, natural language processing, and predictive analytics, can analyze vast amounts of data, uncover hidden patterns, and provide insights that might be missed by human managers.

LITERATURE REVIEW

Constant optimization of commercial processes is still a challenge for firms. In the era of digital transformation, rapidly changing customer expectations for faster delivery and better quality of goods and services, and, economic entities need to improve their internal processes and performance. (Daniel Paschek, 2017) In her paper, Maria Kamariotou says that: AI technology offers great potential to solve difficulties, challenges remain implicated in practical implementation and lack of expertise in the use of Artificial Intelligence at a strategic level to create and increase the value of the economic entity.

Machine learning algorithms process vast amounts of data to uncover patterns, forecast trends, and support real-time decision-making. Managers now rely on predictive analytics for customer behavior, risk assessment, and inventory control.

NLP tools such as chatbots, sentiment analysis, and AI assistants enhance internal and external communications. AI-driven customer service solutions allow for faster, more personalized support, improving customer satisfaction and retention. 2.1 Robotic Process Automation (RPA)

RPA streamlines repetitive administrative tasks such as payroll processing, invoicing, and data entry, freeing managers to focus on strategic priorities. RPA adoption is particularly high in finance, HR, and supply chain operations.

2.1 Robotic Process Automation (RPA)

RPA streamlines repetitive administrative tasks such as payroll processing, invoicing, and data entry, freeing managers to focus on strategic priorities. RPA adoption is particularly high in finance, HR, and supply chain operations.

3. AI and Strategic Management

AI supports data-driven strategy formulation by providing insights into market trends, competitor

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analysis, and scenario simulations. AI tools enable more agile planning, reduce uncertainty, and help anticipate market disruptions.

4. Human-AI Collaboration

AI is not replacing managers but augmenting their capabilities. Managers equipped with AI tools demonstrate improved decision accuracy and faster response times. However, effective collaboration requires digital literacy and continuous training.

5. Challenges and Ethical Considerations

Despite its advantages, AI adoption raises concerns:
- Bias and Fairness: AI systems can inherit data biases, leading to unfair decisions.
- Transparency: The 'black box' nature of some algorithms complicates accountability.
- Job Displacement: Automation threatens certain roles, necessitating upskilling programs.
- Privacy: Data-driven AI must comply with regulations to safeguard user privacy.

6. Case Examples

- Amazon: Uses AI for inventory prediction, dynamic pricing, and personalized recommendations.
- Unilever: Applies AI in recruitment via gamified assessments and NLP-based interviews.
- IBM Watson: Assists in financial forecasting and healthcare diagnostics, supporting managerial insights.

7. Future Outlook

As AI capabilities continue to evolve, future management will involve greater synergy between human intelligence and AI. Key trends include explainable AI (XAI), ethical AI frameworks, and AI-driven innovation ecosystems. Organizations that integrate AI ethically and strategically will be better positioned for sustainable success.

METHODOLOGY

This study adopts a quantitative research methodology, utilizing both primary and secondary data sources. Primary data will be collected through an online survey targeting a diverse group of professionals within the Albanian business sector, including entrepreneurs, market analysts, operational managers, and traders. Secondary data will be drawn from relevant industry publications, business databases, and existing academic literature to supplement and contextualize the findings.

The corporate form of organisation of economic activity is a powerful force for growth. The regulatory and legal environment within which corporations operate is therefore of key importance to overall economic outcomes.
The legislative and regulatory elements of the corporate governance framework can usefully be complemented by soft law elements based on the "comply or explain" principle such as corporate governance codes in order to allow for flexibility and address specificities of individual companies. What works well in one company, for one investor or a particular stakeholder may not necessarily be generally applicable to corporations, investors and stakeholders that operate in another context and under different circumstances. As new experiences accrue and business circumstances change, the different provisions of the corporate governance framework should be reviewed and, when necessary, adjusted.
Corporate governance objectives are also formulated in voluntary codes and standards that do not have the status of law or regulation. While such codes play an important role in improving corporate governance arrangements, they might leave shareholders and other stakeholders with uncertainty concerning their status and implementation.
Artificial Intelligence (AI) has the potential to significantly enhance quality of life by optimizing services across nearly every industry. Despite its promise, AI presents certain challenges - particularly for companies that need to be addressed as businesses increasingly adopt this technology. The integration of AI across different sectors opens up numerous opportunities for both customers and organizations alike.
Graph 1: The Status of Enterprises. Graph 1 presents data on the legal and operational status of various enterprises in the study. It illustrates the distribution of business types among respondents, such as registered companies, informal businesses, or startups.

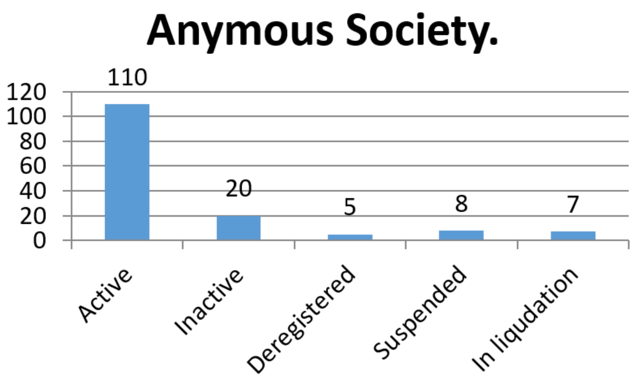

Fig. 1. The Status of Enterprises

This graph will illustrate the size of businesses based on the number of employees. The most common ones seem to be local enterprises in the field of trade, with businesses employing between 10 to 40 employees (with a few businesses employing more than 40). We will also highlight the fact that family businesses are more closed off in their operations (as you mentioned that they perform multiple roles like reception, kitchen, and waiter services).

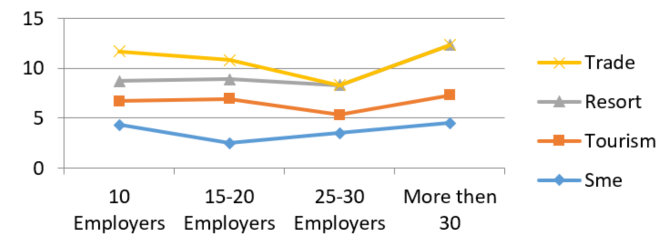

Fig 2: Enterprise Types by Sector and Size.

The second graph shows that the largest percentage are local enterprises in the field of trade, where these enterprises vary in number of employees from 10 to 40 or more. From the interviews we saw that family businesses are more closed from the point of view cyclical because the family members do everything themselves, they work in the hotel, reception, kitchen and waiter services.

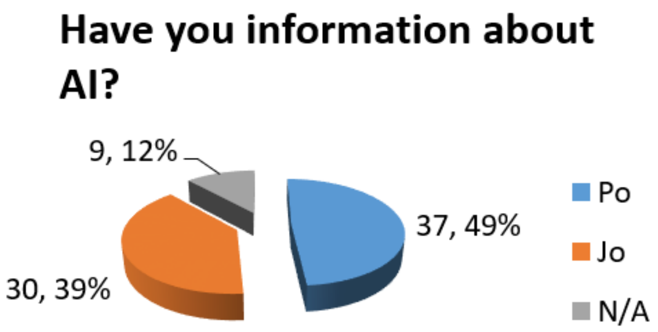

Fig 3: Awareness of Artificial Intelligence.

Graph 3: Awareness of Artificial Intelligence. Graph 3 displays the level of awareness about AI among the respondents. Notably, 37.49% of respondents reported having some knowledge about AI and its applications. This indicates a growing interest and curiosity about the potential of AI, although a significant portion of business owners still lack familiarity with the technology.

The third graph give information about the information of societies, when 37.49% have information about the AI. The same response are and for about corporate governance. This is the specific for this study.

Graph 4: Awareness of Corporate Governance (CG). Graph 4 displays the level of awareness about CG. 37.49% of respondents reported having some knowledge about CG and its applications in their companies.

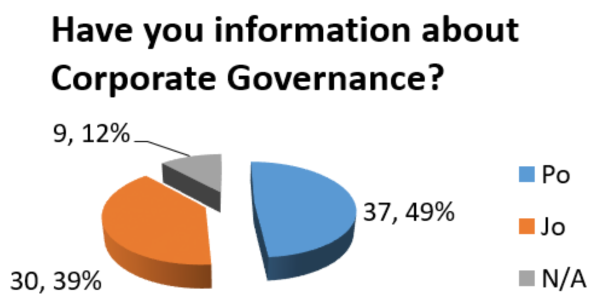

Fig 4: Awareness of CG.

The four graph give information about the information of societies, when 37.49% have information about the CG.30.39% have no information. The information of corporate governance is in the good nivel.

SUGGESTIONS SECTION

Corporate Governance and AI is expected to attract investors to invest their shares in the company at the same time has a great impact on private finance sector. Good governance and AI in a company will foster the welfare of stakeholders and employees who are directly involved in the company. This is intended to create a profitable company. Hence, the company will get added value from high profits. If enterprises have strong governance and AI, the companies will provide more accurate investments with external and internal financial resources. Today is the time of good CG and AI. All the companies has made progress on both of them.

CONCLUSIONS

In order to be effective, the legal and regulatory framework for corporate governance must be developed with a view to the economic reality in which it is to be implemented.

Artificial Intelligence and Corporate Governance are profoundly transforming management practices across various industries. Its ability to enhance decision-making, automate routine tasks, optimize financial operations, and strengthen customer relationships positions AI as a key driver of business evolution. As organizations increasingly adopt AI solutions, they unlock new levels of efficiency, innovation, and competitiveness. However, this transformation is not without challenges. Such issues that particularly affect the employment sector and the process of replacement and job displacement should be looked at more carefully. Another element that requires special attention has to do with data privacy, both for physical and legal entities. (Blogs, 2024) Responsible AI implementation guided by transparency, accountability, and ongoing workforce development is essential to ensure sustainable growth. Organizations should invest in robust AI strategies that balance technological advancement with ethical responsibility. This includes upskilling employees, implementing clear governance frameworks, and continuously evaluating AI systems for bias and fairness. By doing so, businesses can harness AI's full potential while fostering trust and long-term value.

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