11th International Conference of
Management and Industrial Engineering

ISSN 2344-0937
ISSN-L 2344-0937
Volume 11
Website: https://icmie-faima-upb.ro

AN OVERVIEW OF AI AND GEOSPATIAL DATA TOWARDS IMPROVED STRATEGIC DECISIONS AND AUTOMATED BUSINESS DECISION PROCESS

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Abstract: In recent years, the availability and accessibility of geospatial data have greatly increased, providing valuable information for various industries such as transportation, real estate, and retail. However, the great volume and complexity of this data can make it difficult for businesses to extract meaningful insights. By incorporating AI algorithms such as machine learning or deep learning techniques, businesses can more effectively manage, analyze and interpret the data. This paper provides an overview of the current challenges and opportunities in using geospatial data for business decision-making and explores how artificial intelligence (AI) techniques can be applied to better in-form strategic decisions and improve operational efficiency. The study aims to identify best practices and design principles for creating effective automated decision-making systems using AI and geospatial data. A systematic review of the literature was conducted to address the research questions, which revealed that despite challenges, geospatial data presents numerous opportunities for business decision-making. The results suggest that the integration of AI techniques can enhance the efficiency and accuracy of geospatial data analysis, enabling organizations to make more informed strategic decisions. This study highlights the importance of adopting best practices and design principles to maximize the benefits of geospatial data and AI for business decision-making. Overall, this paper argues that the integration of AI and geospatial data analysis has the potential to revolutionize the way businesses make decisions and gain insights from their data.

Keywords: Artificial intelligence; Geospatial data; Decision making, GeoAI: Strategic decisions; Geographic Information System (GIS).

INTRODUCTION

In recent years, the popularity and accessibility of geospatial data has dramatically increased, providing growth opportunities for various industries such as transportation, real estate, retail, services, and hospitality. By incorporating this resource into their business plans, companies can gather large amounts of georeferenced data. However, managing this data can be challenging, and extracting meaningful insights from it will be a significant effort. The integration of AI techniques with geospatial data analysis has the potential to change decisively the way businesses make decisions and gain insights from their data [1].

This paper aims to examine the potential of using AI in conjunction with georeferenced data and geospatial analysis to improve decision making in industrial organizations. The scope is to discuss the challenges and opportunities in using geospatial data for business decision-making, and how AI techniques can be applied to improve data analysis and decision-making processes.

Strategic decisions are crucial for businesses as they help to define the organization's overall direction and long-term goals. Strategic decisions involve identifying and prioritizing objectives, analyzing market trends and competition, and allocating resources to achieve the desired outcomes. These decisions often have significant implications for the business, including financial performance, customer satisfaction, and employee morale. A well-informed strategic decision can help a business to stay competitive, grow and adapt to changing market conditions. On the other hand, a poor strategic decision can lead to significant losses and even threaten the survival of the organization. Therefore, making effective strategic decisions is critical for the success of any business.

AI techniques and geospatial data can support strategic decisions inside businesses by providing valuable insights and enabling better decision-making. Geospatial data, which includes information about the physical location and characteristics of objects, people and activities, can help businesses to understand their operations and markets in new ways. Machine learning or deep learning algorithms can analyze this data to identify patterns, correlations, and trends, which can inform strategic decisions. By combining AI and geospatial data, businesses can gain a deeper understanding of their operations, markets, and customers, which can lead to more effective strategic decisions.

In conducting this research, we aimed to build upon the existing body of knowledge by examining the current challenges and opportunities in using geospatial data for making strategic decisions. We also explored how AI techniques can be applied to geospatial data analysis to improve the decision-making process. During our investigation, we took into account related studies that have individually addressed the challenges [2]–[5], opportunities[6]–[9], and best practices [10]–[13] associated with geospatial data and AI in business decision-making. While these studies have contributed valuable insights separately, our research aims to provide a comprehensive perspective by examining the mutual influence between these elements. Our findings highlight the existing challenges and also underscore the numerous opportunities that lie ahead when integrating geospatial data and AI techniques for strategic decision-making.

The paper is focused on the use of AI techniques with geospatial data in business decision making, in domains like transportation, real estate, and retail. The paper is structured as follows: the second section provides some theoretical considerations based on the current state of the knowledge in the fields of geospatial data and AI in business, the third section describes the methodology used in this research, the fourth section presents the results of the study and the recommendations for all the stake-holders, the fifth section provides the conclusions and future work, and the last section contains the references.

THEORETICAL CONSIDERATIONS

Geospatial data has become increasingly important for business decision making as it enables organizations to identify patterns, trends, and relationships within and between different types of data [14]. However, the effective use of geospatial data poses several challenges, including data quality, data integration, and data visualization [2].

Recent advancements in AI and machine learning have shown promise in addressing these challenges by improving data analysis and decision-making processes. AI techniques, such as neural networks and deep learning, have been applied to geospatial data analysis for a wide range of data that potentially have applications in many fields, such as urban planning, transportation, and environmental monitoring [15]. These techniques have been shown to improve the accuracy and efficiency of geospatial data analysis and decision making [11], [16].

One promising application of AI in geospatial data analysis is the development of automated decision support systems (DSSs). These systems use AI algorithms to analyze large volumes of geospatial data in real-time, providing organizations with timely and accurate insights to support decision making [17].

However, the development of effective automated DSSs using geospatial data and AI requires careful consideration of several design principles and best practices. These include the selection of appropriate data sources, the use of appropriate analytical methods, the incorporation of human expertise, and the implementation of effective visualization techniques [18].

Several studies have also highlighted the need for effective communication and collaboration among stakeholders involved in the design and implementation of automated DSSs. This includes engaging stakeholders in the design process, ensuring the transparency and interpretability of the models used, and providing opportunities for feedback and evaluation [19].

METHODOLOGY

A systematic review of the literature was used to address the research questions and obtain the answers. Systematic literature review can be defined as the process of formally and meticulously review literature based on precise objectives, research questions and a well-defined research strategy [20].

The research questions to be answered by this study are the following:
RQ1: What are the current challenges and opportunities in using geospatial data for making strategic decisions?
RQ2: How can AI techniques be applied to geospatial data analysis to improve the decision-making process?
RQ3: What are the best practices and design principles for creating effective automated decision-making systems using AI and geospatial data/ geographic information systems (GIS)?
An extensive search was conducted using four digital databases that ensured depth for the literature search, ensured a more thorough examination of the relevant research, and increases the overall robustness of the study: MDPI Journals, Web of Science, Scopus and BASE (Bielefeld University Library). The search was conducted with no time restrictions (distributed in time as depicted in Figure 1) and the search terms included keywords related to geospatial field, AI and business strategic decisions and decision-making process. The terms from each category were integrated in the queries by the Boolean operator AND. The search was limited to papers written in English language. Articles were included if they addressed the research questions and were published in peer-reviewed journals or conference proceedings. The articles had to be original research studies, review papers, or case studies that focused on the use of geospatial data, AI, strategic decisions and business decision-making. Articles were excluded if they were not relevant to the study, or were not written in English. A total of 102 works met the inclusion criteria.

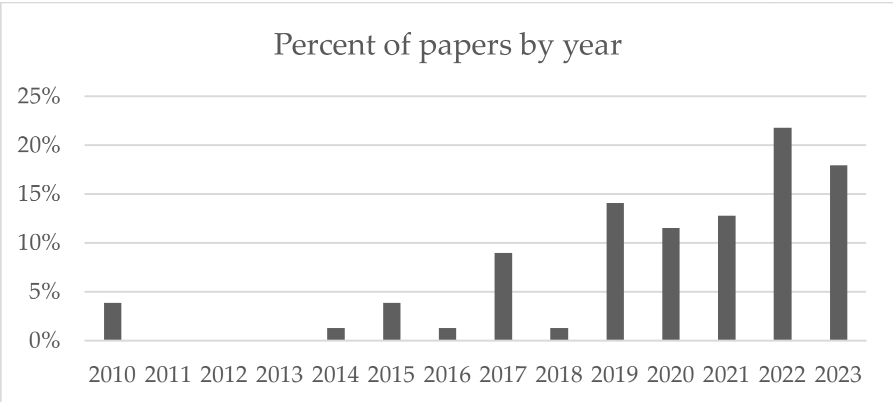

Figure 1: Percent of papers, by year. Source: authors' work

The data extraction process included collecting relevant information from the selected articles, including study design, data sources, analytical methods, and key findings related to the research questions. The extracted data were synthesized and analyzed using a thematic analysis approach. The analysis focused on identifying the challenges, opportunities, and best practices related to the use of geospatial data and AI in business decision making and to better inform strategic decisions (pointed out in Figure 3). A relevant word cloud was created with the words from titles, keywords and abstracts of the papers, as shown in Figure 2.

Figure 2: Word cloud from titles, keywords and abstracts. Source: authors' work

RESULTS

As it can be seen in Figure 2, the word *data* is the most important in the reviewed papers, indicating that the data is to be the main focus for scientists and practitioners in the studied matter and represents the keyword towards the answers to the researched questions. Geospatial data has become an increasingly valuable resource for businesses in making informed decisions. It offers a wealth of information that can be used to better understand customer behavior, market trends, and geographical variations in demand and supply [21]–[25]. However, the use of geospatial data for business decision making is not without its challenges. Figure 3 reveals the distribution of the main focus of selected papers, in percent.

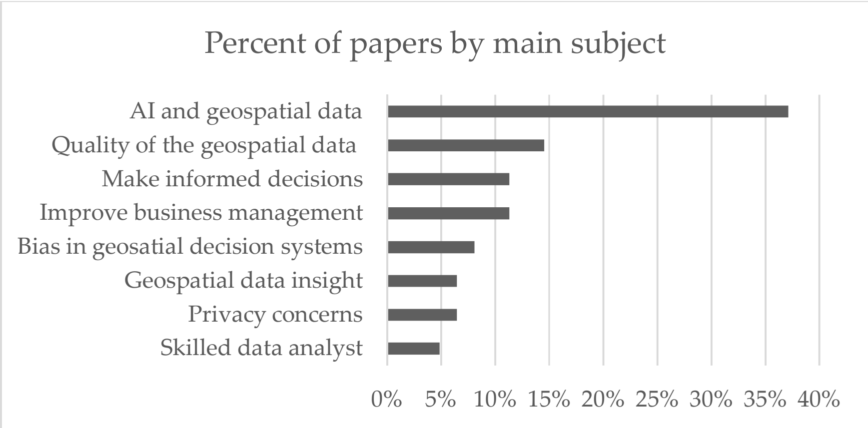

Figure 3: Percent of papers, by main subject. Source: authors' work

DISCUSSION

5.1. Current challenges and opportunities in using geospatial data for making strategic decisions

One of the key challenges in using geospatial data is the quality of the data itself. Geospatial data can be complex and varied, and it often requires significant effort to process and analyze. Errors in data collection and processing can also lead to inaccurate results, which can have serious consequences for decision making [3], [10], [26], [27]. These challenges reveal the importance of data quality control and assurance in geospatial data analysis. Organizations must invest in robust data validation and cleaning processes to minimize inaccuracies in decision-making, emphasizing the critical role of data quality. Another challenge is the need for specialized skills and expertise. The effective use of geospatial data requires a thorough understanding of geospatial technologies, data management and analysis tools, and statistical methods. Businesses may need to invest in training and development programs to ensure that their staff have the necessary skills to work with geospatial data [4], [28]. This challenge highlights the importance of building a skilled workforce capable of handling geospatial data. To address this challenge, businesses need to provide ongoing training to their employees or recruit experts in geospatial data analysis. Privacy concerns are also a challenge. Geospatial data can be highly sensitive, and businesses need to take measures to protect the privacy of individuals and organizations represented in the data [5], [25], [29]. This can involve implementing strict data access policies, anonymizing data, and complying with relevant data protection laws and regulations. Businesses and organizations need to be aware of the ethical and legal responsibilities associated with geospatial data. Implementing privacy measures not only ensures compliance but also maintains the trust of individuals and organizations whose data is included in geospatial datasets.

These challenges are interconnected, as addressing data quality, specialized skills, and privacy concerns can collectively lead to more effective and responsible use of geospatial data in decision-making. Additionally, by recognizing these challenges and working towards solutions, organizations can unlock the full potential of geospatial data for improved strategic decision-making.

Despite these challenges, the use of geospatial data to better inform strategic decisions presents numerous opportunities. Geospatial data can provide businesses with valuable insights into customer behavior and preferences,

allowing them to tailor their products and services to meet customer needs more effectively [6], [30]. The ability to customize products and services based on geospatial data-driven insights can enhance customer satisfaction and loyalty. It also contributes to more efficient resource allocation, ultimately impacting the overall performance.
Geospatial data can also be used to optimize supply chain management, improve logistics and transportation, and identify new market opportunities [7], [8], [31]. Moreover, advancements in AI and machine learning are making it easier for businesses to work with geospatial data. These technologies can be used to analyze large amounts of data quickly and accurately, enabling businesses to make better-informed strategic decisions in a timely manner. Geospatial data presents a wealth of opportunities for businesses, from understanding customer behavior to optimizing supply chains and identifying new market opportunities. The integration of AI and machine learning further enhances the value of geospatial data by providing quick and accurate insights for more effective and timely decision-making. These insights are instrumental in enhancing competitiveness, improving customer satisfaction, and driving business growth.

5.2. AI techniques, applied to geospatial data analysis to improve the decision-making process

Artificial Intelligence (AI) techniques can be applied to geospatial data analysis to improve decision making in a number of ways [7], [11], [13], [26], [31], [32]. Recent studies have demonstrated the potential of AI for analyzing and interpreting geospatial data, and there are many successful applications of these techniques in various fields [7], [31], [33], [34].
One key area where AI techniques have been successful is in the analysis of satellite imagery. Researchers have used deep learning algorithms to analyze satellite images of crop fields, allowing them to predict crop yields and monitor agricultural productivity over time. This has the potential to improve crop management and increase yields, which can be of significant economic value. Another area where AI is being applied to geospatial data analysis is in transportation and logistics. By analyzing traffic patterns, AI algorithms can optimize routes for delivery trucks, reducing transportation costs and improving delivery times [8], [31], [35]. In addition, AI can be used to analyze weather patterns and other environmental factors, helping companies to better plan and manage their logistics operations. AI can also be used to analyze customer behavior and preferences based on geospatial data. For example, by analyzing social media posts and geolocation data, businesses can gain insights into customer preferences and behaviors, allowing them to develop more targeted marketing strategies [25]. Recent studies have also explored the use of AI for land use planning and urban development [11], [32], [34]. By analyzing geospatial data on land use, population density, and other factors, AI algorithms can provide insights into how cities and towns can be designed and developed to optimize livability and sustainability.
The success of AI techniques in geospatial data analysis is versatile, spanning various fields. Techniques developed for one domain, such as agriculture, can be adapted and applied in others, exemplifying the adaptability and transformative potential of AI in enhancing decision-making across industries. The application of AI in geospatial data analysis has far-reaching implications, from economic benefits, such as improved crop management and reduced transportation costs, to environmental considerations like optimizing routes and land use for enhanced livability.

5.3. Best practices and design principles to create effective automated decision-making systems

Creating effective automated decision systems using AI and geospatial data requires a thorough understanding of best practices and design principles. By following these practices, businesses and organizations can ensure that their decision systems are accurate, efficient, and reliable.
One best practice is to ensure that the data used in the decision system is of high quality. This involves verifying the accuracy of the data, eliminating outliers, and addressing any missing data [4], [10]. Additionally, it is important to ensure that the data is representative of the problem being solved and that it is updated regularly. High-quality, representative data is the foundation of any AI-driven decision system. Without accurate and relevant data, the system's outcomes may be compromised. Another important principle is to choose the right AI algorithm for the specific problem being solved. Different algorithms have different strengths and weaknesses, and it is important to select the algorithm that is best suited for the task at hand. For example, deep learning algorithms may be more effective for image recognition tasks, while decision tree algorithms may be better suited for classification tasks. It is

also important to evaluate the performance of the decision system on a regular basis. This involves comparing the output of the system to ground truth data and assessing the accuracy and reliability of the system [13], [35]. If necessary, adjustments should be made to the system to improve its performance.
In addition, it is important to address issues of bias in the decision system. Bias can arise from the data used to train the system, and it is important to ensure that the data is representative of the population being studied. Additionally, it is important to ensure that the system is transparent, so that users can understand how the system arrived at its decisions. Addressing bias and ensuring transparency are critical for ethical and fair decision systems. These aspects also enhance user trust and accountability.
Finally, it is important to ensure that the decision system is designed to meet the needs of the users. This involves understanding the requirements of the users and de-signing the system accordingly. The system should be easy to use, provide clear feedback to users, and be flexible enough to adapt to changing requirements.

CONCLUSION

Geospatial data has become an increasingly valuable resource for businesses in making informed decisions. However, its effective use for business decision making is not without challenges. One of the key challenges is the quality of the data itself, as it can be complex and varied, and errors in data collection and processing can lead to inaccurate results. Another challenge is the need for specialized skills and expertise, which may require businesses to invest in training and development programs. Despite these challenges, geospatial data presents numerous opportunities, such as providing valuable insights into customer behavior and preferences, optimizing supply chain management, and identifying new market opportunities. Advancements in AI and machine learning are making it easier for businesses to work with geospatial data by analyzing large amounts of data quickly and accurately. These findings answer to the first research question: *What are the current challenges and opportunities in using geospatial data for making strategic decisions?*
AI techniques can be applied to geospatial data analysis to improve decision making in several ways. One key area where AI techniques have been successful is in the analysis of satellite imagery, allowing researchers to predict crop yields and monitor agricultural productivity over time. AI can also be used in transportation and logistics to optimize routes for delivery trucks and analyze weather patterns and other environmental factors. In addition, AI can be used to analyze customer behavior and preferences based on geospatial data, allowing businesses to develop more targeted marketing strategies. This answers to the RQ2: *How can AI techniques be applied to geospatial data analysis to improve the decision-making process?*
Best practices and design principles can ensure that automated decision systems using AI and geospatial data are accurate, efficient, and reliable, including ensuring high-quality data, choosing the right AI algorithm for the specific problem being solved, evaluating system performance on a regular basis, and addressing issues of bias. Geospatial data, when used effectively with AI and machine learning, can provide businesses with valuable insights that enable better-informed strategic decisions. While challenges such as data quality and specialized expertise exist, advancements in technology present numerous opportunities to improve business decision-making. By following best practices and design principles, businesses can ensure that their auto-mated decision systems using geospatial data and AI are accurate, efficient, and reliable, leading to better outcomes and increased success. This answers the third research question: *What are the best practices and design principles for creating effective automated decision-making systems using AI and geospatial data/ geographic information systems (GIS)?*
By addressing challenges with best practices can lead to the realization of opportunities in strategic decision-making. This review study also highlights the interdependence of these elements, where effective practices mitigate challenges and enable businesses to seize opportunities.
Limitations of this review paper include the possibility of publication subjectivity and the potential limitations of the search strategy, and might have generated omissions. Additionally, the findings of this review paper may be limited by the quality and scope of the selected articles.
From the review of the literature, we have identified some *literature gaps*: there were no studies that compared the efficiency of AI use in geospatial analysis, there were very little words about the ethical impact of the use of AI methods in business decision-making, and none of the works selected for this study was centered on decision systems based on end-user profile.

Geospatial data analysis and AI techniques span multiple disciplines, including computer science, geography, and business. *Future research* can promote interdisciplinary collaboration to leverage expertise from different domains and develop innovative solutions for decision-making. Future research could also compare the effectiveness of different AI techniques for geospatial data analysis. This would help practitioners to choose the most appropriate technique for their specific needs and improve the overall effectiveness of geospatial data analysis. Future studies could provide a more detailed and comprehensive list of best practices and design principles for creating effective automated decision-making systems. This would provide practitioners with more practical guidance on how to design such systems. The use of real-time geospatial data can significantly enhance decision-making processes. Future research can explore ways to integrate real-time data sources, such as IoT sensors, social media feeds, and satellite imagery, into AI models for more timely and accurate insights. As the use of AI and geospatial data becomes more prevalent, ethical considerations become increasingly important. Future research should focus on understanding and addressing ethical challenges, such as privacy concerns, biases in AI algorithms, and the impact of AI-driven decisions on society. The design of AI-driven decision support systems should prioritize user needs and preferences. Future research can explore user-centric design approaches to ensure that decision systems are intuitive, transparent, and adaptable to user requirements.

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