https://doi.org/ 10.7251/EMC2502535S

UDK: 005.311.6:659.126

Datum prijema rada: 25. avgust 2025.
Submission Date: August 25, 2025
Datum prihvatanja rada: 15. decembar 2025.
Acceptance Date: December 15, 2025

Časopis za ekonomiju i tržišne komunikacije
Economy and Market Communication Review

Godina/Vol. **XV** • Br./No. **II**
str./pp. 535-546

PREGLEDNI NAUČNI RAD / OVERVIEW SCIENTIFIC PAPER

BUSINESS INTELLIGENCE MODEL FOR MULTIDIMENSIONAL ANALYSIS OF THE INSURANCE MARKET BASED ON OPEN DATA

Ana Šego Doctoral Studies, University of Mostar, Mostar Bosnia and Herzegovina, Agram d.d. Ljubuški, mag.ing.inf et comm.techn., college Lecturer, College "Logos centar" Mostar, Bosnia and Herzegovina, ana.sego1@phd.sum.ba, ORCID ID 0009-0007-2440-5044

Maja Gakić Doctoral Studies, University of Mostar, Mostar Bosnia and Herzegovina, College "Logos centar" Mostar, mag.ing.comp., college Lecturer, College "Logos centar" Mostar, Bosnia and Herzegovina, mgakic@phd.sum.ba , ORCID ID 0009-0000-2386-4205

Davor Škobić mag.ing.comp. college lecturer, College "Logos centar" Mostar, Endava d.o.o. Sarajevo, Bosnia and Herzegovina, davor.skobic@gmail.com , ORCID ID 0009-0002-1015-9798

Abstract: *This paper explores the role of open data and business intelligence (BI) in analyzing the insurance market, with a specific focus on Bosnia and Herzegovina. Using available vehicle registration data, a system has been developed that enables territorial and temporal analysis of insurance companies' market shares. The system contributes to making informed business decisions through an overview of key indicators, such as the number of policies issued, changes compared to previous periods, and the geographic distribution of the market. The use of open data has enhanced transparency, accessibility, and repeatability of analysis, thereby encouraging broader adoption of analytical tools. The system does not require advanced analytical knowledge from users but facilitates result interpretation through visual indicators and automated reports. In addition to presenting the existing solution, the paper proposes expanding the system through the application of artificial intelligence, including predictive analysis, market segmentation and identification of customer churn risk. The proposed model shows how open data can serve as the basis for powerful BI systems, accessible even to smaller organizations, with the potential for wider application in the public sector, industry and scientific research. This paves the way for intelligent business analytics that support strategic decision-making, improve efficiency, and promote the development of data-driven practices.*

Keywords*: business intelligence, artificial intelligence, open data, analytics, insurance*

JEL classification*: C88, G22, L86, C81, O33*

INTRODUCTION

Business intelligence (BI) is widely applied across various business functions, including marketing, sales, finance, and operations, to support data-driven decision-making and enhance performance. As BI continues to evolve, emerging technologies and trends significantly influence its implementation within organizations (Kilanko, 2022). It relies on a combination of tools and methods to collect data from internal and external sources, transform it into actionable insights, and present it in a comprehensible format for decision-makers (Kilanko, 2023). The growing importance of processing both structured and unstructured data has led to advancements in data visualization and reporting tools, enabling more interactive and personalized insights (Mungoli, 2023). The integration of Big Data and artificial intelligence into BI systems has further improved analytical capabilities and operational efficiency (Bharadiya, 2023; Bickley, 2025). Over time, BI systems have progressed through four generations, culminating in intelligent business analytics (IBA) that enable real-time, AI-driven decision-making. These advanced systems embed analytics directly into business processes, allowing managers to act on system-generated recommendations without requiring deep analytical expertise, thus improving responsiveness to market dynamics (Azvine, 2003; Sun, 2022). Today organizations face increasing pressure to make timely decisions based on large volumes of data. This is particularly relevant in the insurance sector, where market complexity, strong competition, and evolving client expectations demand accurate and agile decision-making. Analyzing market share by geographic regions and over specific time periods is essential for strategic planning and operational control. This paper presents the development of an application for insurance market analysis in Bosnia and Herzegovina, with a focus on territorial (municipality, canton, entity, country) and temporal dimensions (current year versus previous year). The application provides insights into market shares and their trends over time, thereby supporting more informed managerial decisions. The theoretical foundation of the work is based on the principles of business intelligence, decision support systems, performance management, and geographic analytics.

THEORETICAL BACKGROUND

Business Intelligence (BI) implies the process of identification of the informational needs of decision-makers, collecting relevant data in a legal and ethical manner, and its analysis and delivery in a secure and applicable form (Klepić, 2020). In combination with Industry 4.0 technologies, BI contributes to the increase in competitiveness, operational efficiency, and decision-making quality *(Kongthanasuwan, 2023)*. BI systems enable the identification of trends, patterns, and anomalies, and in the context of insurance market analysis, they make the visualization of market shares across territorial and time dimensions, and the recognition of growth potential easier.

Open data is defined as information available to everyone without legal or technical restrictions (Kitchin, 2014), with its key advantage lying in enhanced transparency, with the obligation to respect ethical and legal standards (Huber, 2022; Jetzek, 2014; Weerakkody, 2017). In the BI context, open data provides insight into market flows and customer behavior, and through the application of advanced analytical methods (e.g., machine learning, predictive analytics), it supports data-driven decision-making *(Stodolsky, 1982).* For example, the analysis of vehicle registration data and insurance

premiums can stimulate the development of risk assessment models in the insurance sector (IDDEEA & Agency, 2025). Open data also enables the verification and replication of analytical procedures, thereby increasing trust in the system and facilitating the development of similar solutions, especially for smaller organizations without access to proprietary databases and expensive tools.

By utilizing open data, analytical results can be replicated and verified, which boosts trust in the system and encourages the development of similar solutions in other contexts. This also reduces dependency on closed, commercial data sources, which is particularly important for small and medium-sized organizations lacking access to costly analytical tools or internal data repositories. In this approach, the BI system evolves toward open business intelligence, where the data foundation comes from publicly available sources, and analytical capabilities become accessible to a wider user community. In the context of the insurance industry, there are numerous publicly available sources of information, but publications from regulatory bodies in the insurance sector are particularly important. These publications provide both an overview of the historical development of the market and insights into its current state. In this case, open data from the Agency for Identification Documents, Registers and Data Exchange (IDDEEA) is used for analyzing the insurance market in Bosnia and Herzegovina (IDDEEA &Agency, 2025). The next chapter explains what IDDEEA is, how it collects data, and how that data was acquired and processed for business purposes.

Decision Support Systems (DSS) are defined as computer-supported systems that help managers process structured and unstructured data (Gorry, 1971; Stodolsky, 1982). Later upgrades (Liang, 2011; Sprague, 1980) incorporate BI functions such as multidimensional analysis and interactive visualizations. The application presented in this paper is based on these principles: it enables tracking of key market indicators across administrative units (e.g., municipality, canton) and visual coding of changes (e.g., red–decline, green–growth), allowing users to make fast and intuitive decisions without advanced analytical knowledge.

Socio-technical systems theory *(Emery, 1959)* emphasizes the importance of balance between technical solutions and human interaction. I accordance with this theory, the application is designed to increase the accessibility of analytical insights and to facilitate the use of BI systems among non-technical users. This is also linked to the concept of cognitive offloading (Risko, 2016), which involves passing on parts of the thinking process to external systems—in this case, analytical software that transforms data into productive insights.

In the context of decision-making under uncertainty *(Simon, 2013)* Decision Support Systems (DSS) assist managers in taking action despite incomplete information and limited cognitive capacities (Humphreys, 2013). The Business intelligence (BI) model developed in this study reduces the level of uncertainty by integrating visual and quantitative indicators. The use of geographic data in business decision-making is based on the concept of location intelligence, which is considered a part of the broader BI framework. Analyzing data by geographic units (e.g., municipality, county) enables targeted decision-making for specific regions and the recognition of regional trends in the insurance market.

Finally, the theory of information value *(Lambe, 2011)* emphasizes that information holds real value only when it contributes to more effective decision-making.

The BI system developed in this study confirms this theory by transforming open data into contextualized information that serves as a foundation for strategic and operational business decisions.

ANALYSIS OF THE BI MODEL FOR OPEN DATA PROCESSING

One of the key features of the developed system is its reliance on open data - publicly available datasets published by government institutions and regulatory bodies. Open data represents an important starting point for creating analytical systems that are scalable, transparent and accessible to various stakeholders, including the private sector, academia and public organizations *(Janssen et al., 2012)*.

The Agency for Identification Documents, Records, and Data Exchange of Bosnia and Herzegovina (IDDEEA) regularly publishes data on registered vehicles, which is publicly available on its official website. You can see the data structure in Table 3.

This data comes in handy for a detailed analytics affair in the insurance market within the space of the country, indicating numerous aspects with regard to insured vehicles and their policies.

Table 1. Structure of data published in the IDDEEA bulletin

Column	Description
Request Type	Request type codebook
Registration Location	Municipality codebook in BiH
Vehicle Brand	Vehicle brand codebook
Vehicle Type	Vehicle type codebook
Vehicle Model	Vehicle model codebook
Vehicle Color	Color codebook
Vehicle Category	Vehicle category codebook
Vehicle Purpose	Purpose codebook
Body Type	Body type codebook
Year of Manufacture	Whole number, year
Engine Displacement	Whole number, cc
Maximum Engine Power	Whole number, kW
Fuel Type	Fuel type codebook
Eco Characteristics	Eco standard codebook
Catalyst	Y/N
Empty Vehicle Mass	Whole number, kg
Allowed Payload	Whole number, kg
Maximum Allowed Total Mass	Whole number, kg
Number of Axles	Whole number
Number of Driven Axles	Whole number
Number of Wheels	Whole number
Seating Capacity	Whole number
Standing Capacity	Whole number
Ownership	Codebook
Insurance	Codebook

Source: Authors, based on Structure of Data Published in the IDDEEA Bulletin.

A data warehouse is a centralized database entitled to house disparate records from different subject areas for the purpose of assisting in decision making. It enables total access, both historical and current, to users, who may analyze it based on the user's request and make decisions accordingly. Primarily, transaction data and processed data is time-variant and nonvolatile (Inmon et al., 2010; Sreemathy et al., 2021). In the middle of the data warehousing process is the ETL, which is extract-load-transformed. This involves bringing data together from various sources to include data cleansing and organization with the business rules as required by the formats already available in the data warehouse. Originally, these were directed towards data integration and computation, now, ETL prepares data for business intelligence and analytics while it ensures consistency and quality of data (Bergamaschi et al., 2011; Biplob et al., 2018).

An organization will frequently employ ETL to:

- Extract data from legacy systems
- Cleanse the data to improve data quality and establish consistency
- Load data into a target database

ETL processes are essential for ensuring data quality by cleansing and organizing raw information to remove inconsistencies and errors. These systems are designed to operate at scale, efficiently managing large volumes of data originating from diverse sources. By delivering structured and reliable datasets, ETL supports business intelligence and analytical processes, enabling more informed decision-making. Additionally, the implementation of automated workflows within ETL minimizes the need for manual intervention, thereby improving operational efficiency and consistency *(El-Sappagh et al., 2011).*

By leveraging this open data, a software solution has been developed to generate tabular and graphical reports through a web application. The system is designed to provide precise market analysis by utilizing the following input parameters:

Period from (month and year) – the start date for the analysis,

Period to (month and year) – the end date for the analysis,

Territory of interest – the ability to analyze data at the level of the country, entity, or canton/district,

Ownership type – classification of vehicles based on ownership (private individuals, legal entities, or the entire market).

Figure 1 System architecture

Source: Authors

For implementing Microsoft SQL Express 2022, the database management system was leveraged, while reports were visualized using Microsoft SSRS (SQL Server Reporting Services). The business logic developed through using a SQL programming

language in the database automatically updates data in machine-readable format on a monthly basis.

With a web-based user interface, the system is open to insurance companies and other stakeholders to keep track of market trends, changes occurring therein, and take informed business decisions. This data-processing model can also be extended to assess premium potential, market shares for vehicles, and factors influencing vehicle insurance in Bosnia and Herzegovina (Škobić & Šego, 2023).

Each report contains the following basic data, visible in the tables.

Table 2. Overview of the number of polices for the selected territory and period

Column	Description
Current Year	Whole number
Previous Year	Whole number
Difference	Whole number
Index	Difference

Source: Authors based on Škobić & Šego, 2023

Table 3. Statistic for the selected territory and period

Column	Description
Insurance	Insurance name
Number of Policies CY	Whole number
Number of Policies PY	Whole number
Difference	Whole number
Index	Index
Share CY	Percentage
Share PY	Percentage
Difference Share	Percentage

Source: Authors based on Škobić & Šego, 2023

TESTING AND VALIDATION

The application for calculating market shares of insurance companies underwent several testing phases to ensure accuracy. Functional testing confirmed correct market share calculations using data sourced from open data (IDDEEA) after an ETL process. Manual checks showed deviations of less than 0.2% for one month's data, with a comparison to the "First Release of Registered Road Motor Vehicles for 2024" by the FBiH Institute for Statistics showing deviations of less than 0.7%. The application processed data (6,038,851 vehicle registrations from 01.01.2020 to 31.01.2025) in an average of 7 seconds for demanding operations. Robustness testing confirmed resilience to incorrect or missing data. User feedback highlighted potential interface improvements. Data for 2024 is available on the FZS website (Federal Bureau of Statistics, 2025).

DISCUSSION AND RECOMMENDATIONS FOR FUTURE RESEARCH

The developed business intelligence model for analyzing the insurance market in Bosnia and Herzegovina confirms the theoretical basis of business informatics

through the application of business intelligence, decision support systems, open data, location intelligence and key performance indicators. The model enables detailed analysis of market shares by territorial and time units, visualization of changes and creation of automated reports, thus providing managers with concrete support in decision-making. The business intelligence system was applied to transform raw and open data into useful, operational information.

The paper also confirms the elements of a decision support system through the processing of structured and unstructured data, which enables support for semi-structured business decisions. Location intelligence is used through geographically based displays of market data, while key performance indicators, such as market share, annual growth and portfolio stability, are consistently applied in accordance with the concept of balanced scorecards. The use of open data published by government institutions contributes to transparency, repeatability of analysis and wider availability, thus confirming the concept of open business intelligence.

In addition to the basic theoretical frameworks, the system also validates additional approaches. According to the information value theory, data only gains its true value when it is contextualized and interpreted for decision-making purposes. In conditions of market fluctuations and competitive dynamics, the system provides clarity and decision-making support in uncertain circumstances. Also, through the application of socio-technical principles, the application design enables ease of use, with visual cues and automated insights helping users without technical knowledge make informed decisions, thereby reducing the need for specialized analytical support.

Although the developed system represents a powerful tool for insurance market analysis, its accuracy is limited by the absence of certain data. Most notably, there is a lack of demographic information about vehicle owners, which would enable more effective segmentation and personalization of insurance offers. Additionally, since the data is available only on a monthly basis, tracking short-term market dynamics is constrained; daily or weekly insights would allow for more agile responses. The system also does not include information on previous insurance policies, which hinders the assessment of customer loyalty and the prediction of churn. Nevertheless, some behavioural patterns can be inferred by linking multi-year records based on the technical characteristics of vehicles. Furthermore, integrating the system with internal datasets from insurance companies could help bridge some of these data gaps and provide a more comprehensive view of clients, premiums, and insurance history.

Beyond its primary function of market share analysis, the system also supports broader analyses that may benefit other sectors, such as the automotive industry or public administration. Through a multidimensional analytical approach, it is possible to examine interdependencies between vehicle specifications, geographic distribution, and temporal trends. Based on available vehicle data, it is feasible to approximate the premium potential of specific regions, taking into account the calculation model for motor third-party liability insurance in Bosnia and Herzegovina. In this way, the system extends beyond its initial scope and emerges as a strategic analytics tool with wider applicability.

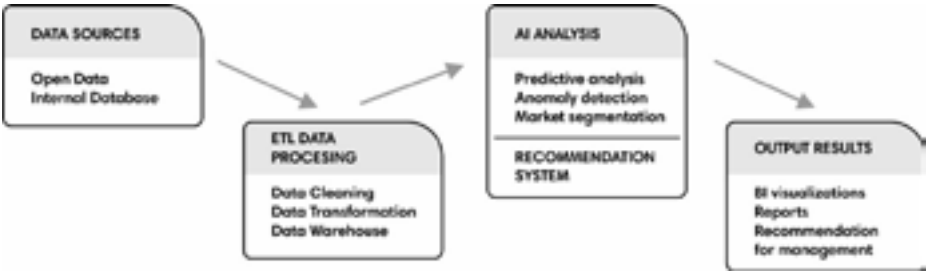
The integration of artificial intelligence (AI) and data analytics into business intelligence (BI) marks a key shift in the way business strategies and decision-making processes are developed. Žigienė et al. (2022) emphasize that this connection leads

to the creation of intelligent business analytics (IBA), which combines traditional BI with advanced AI and big data technologies (Žigienė et al., 2022). This transition to BI enables organizations to better manage data and make more informed decisions. According to the authors, intelligent business analytics represents a new dimension of BI that uses the potential of AI and big data to improve business decisions and strategic planning (Bickley, 2025; Syed et al., 2021).

Artificial intelligence (AI) is significantly transforming business intelligence (BI) systems, particularly in decision support. Through predictive modeling, machine learning, and automation, AI enhances data analysis efficiency and reveals hidden patterns (Eboigbe et al., 2023). This has enabled the development of self-service BI models, allowing non-technical users to generate insights and make data-driven decisions independently. Integrating AI into BI applications provides advanced analytical capabilities. AI algorithms automate data processing, identify patterns, and produce predictive insights that support informed business decisions (Ghasemaghaei, 2019). By leveraging technologies such as computer vision, machine learning, and natural language processing (NLP), AI can analyze both structured and unstructured data, including images, language, and video, thus broadening the analytical scope (Bharadiya, 2023). This synergy between AI and BI extends access to advanced analytics beyond large enterprises, fostering data democratization and promoting a culture of data-driven decision-making across organizations of all sizes (Chintala, 2024).

In this chapter, the proposal is made for upgrading the currently existing analytical system of the insurance market in Bosnia and Herzegovina through artificial intelligence. The usage of AI models is intended to advance the analysis of trends in the market and competition and also the geographical distribution of the insurance market. The actual implementation, however, is not in the purview of this work; it provides a specific target model that then serves concrete guidelines for an accurate improvement of business decision-making, as well as the optimization of existing analytical methods.

Figure 2. System architecture – development of AI- Driven BI system



Source: Authors

The system upgrade proposal may integrate key AI technologies for market analysis and strategic decision-making. Predictive analysis leverages machine learning models like ARIMA, Linear Regression, Random Forest, and Gradient Boosting to forecast seasonal fluctuations and market trends (Cheng et al., 2020; Ogunleye, 2023). Anomaly detection uses Isolation Forest and Autoencoders to identify unusual market changes, while K-means and DBSCAN clustering detect regions under abnormal conditions (Gupta & Tripathy, 2024; Hairach et al., 2023). Market segmentation

is achieved through K-means and DBSCAN, with neural networks optimizing personalized offers *(Hossain, 2017).* AI recommendation systems employ collaborative and content-based filtering to dynamically adjust business strategies, marketing campaigns, and policies in response to market shifts (Fayyaz et al., 2020).

As part of the proposal for further research and improvements to the insurance market analysis model, this paper relies on existing approaches and previous studies in machine learning and social network analysis. Škobić et al. (2020) examined the use of machine learning algorithms such as logistic regression, decision trees, and deep learning to analyze the profitability of casco insurance customers *(Škobić et al., 2020).* The results showed that decision trees had the highest accuracy (92.44%), while logistic regression was most effective in identifying unprofitable clients. A possible improvement to this model could include extending the analysis to mandatory auto liability insurance using IDDEEA data, allowing for customer profitability predictions by geographic regions and the optimization of premium pricing.

Another perspective on the proposed upgrade relates to churn rate detection based on the research conducted by Mandić et al. (2018) analyzing social networks of telecommunications service users. As noted, churn refers to the rate of loss of customers or users over a certain period of time *(Mandić et al., 2018).* For insurance, churn is a performance indicator on how well a company maintains its customer base, and customer loyalty is one of the top priorities. Several studies in the insurance industry have indicated that long-term clients require less time and that it is cheap to retain them compared to acquiring new ones (Bolancé et al., 2016).

Customer data are extremely valuable to insurance, and insurance companies have a lot of information about their customers. Therefore, a similar approach could be applied in the insurance sector by linking multi-year data from the IDDEEA database (which contains vehicle registration information) with insurer databases to identify key factors influencing churn rate and locations with the highest risk of customer loss. By connecting data using a generated key based on vehicle characteristics (registration municipality, brand, engine type, color), it would be possible to identify high-risk churn customers from the insurance database and develop a predictive model for customer attrition. This approach could be particularly beneficial for smaller communities, where the likelihood of many vehicles sharing identical characteristics is low. Notably, nearly 60% of municipalities in Bosnia and Herzegovina have fewer than 20,000 residents, while over 87% have fewer than 50,000 (Federalni zavod za statistiku BiH, 2025). Insurers may apply this approach to create tailored retention solutions such as some off-benefits available to a particular segment or even targeted marketing campaigns. Linking internal insurance data with identified churn customers would help optimize business strategies further, thus raising profitability.

CONCLUSION

This paper presents a tangible contribution of business informatics to the development of a system that leverages open data and BI tools for analyzing the insurance market in Bosnia and Herzegovina. Core components such as BI systems, decision support systems, location intelligence, and KPIs were successfully integrated into an application that enables multidimensional market analysis and data-driven decision-making. Visualizations and automated reporting facilitate interpretation and

reduce dependency on analytical experts, thereby reinforcing the socio-technical design principles of information systems. The system also supports information value theory—raw, open data attain business value only when interpreted in a meaningful context. The theory of decision-making under uncertainty is confirmed by the system's ability to help users detect market changes and risks even without complete data certainty. Ultimately, the system demonstrates how open data can form the foundation of effective BI systems accessible even to small organizations. The enhancement proposed through artificial intelligence extends the system's functionality into the domain of predictive analytics, anomaly detection, identification of regional patterns, and the generation of managerial recommendations. In doing so, the system is transformed into an intelligent analytical tool capable of significantly improving business strategy. Beyond insurance companies, this model holds substantial potential for public administration, the automotive industry, the transport sector, and the academic community particularly in the areas of market research, user behavior analysis, and the development of public digital solutions. It is also relevant for startups and the IT sector engaged in the development of data-driven services. In this way, the model transcends the boundaries of the insurance sector and becomes a tool for digital transformation in a broader socio-economic context. Future research should focus on evaluating the upgraded system in real-world business settings, as well as developing modules for customer churn detection, offer personalization, and dynamic market segmentation. The success of such systems will depend on achieving a balance between analytical sophistication and transparent, ethical data governance a continuing challenge in the field of business informatics.

LITERATURE

Azvine, B., Nauck, D., & Ho, C. (21 2003). Intelligent business analytics—a tool to build decision-support systems for eBusinesses. *BT Technology Journal*, str. 65–71.

Bergamaschi, S., Guerra, F., Orsini, M., Sartori, C., & Vincini, M. (8. 70 2011). A semantic approach to ETL technologies. *Data & Knowledge Engineering*, str. 717–731.

Bharadiya, J. P. (2023). Machine learning and AI in business intelligence: Trends and opportunities. *International Journal of Computing, 48*(1), str. 123-134.

Bickley, S. J., Macintyre, A., & Torgler, B. (2025). Artificial intelligence and big data in sustainable entrepreneurship. *Journal of Economic Surveys, 1*, str. 103–145.

Biplob, M. B., Sheraji, G. A., & Khan, S. I. (2018). Comparison of different ETL tools for R data warehousing. *International Conference on Innovative Science, Engineering and Technology*, (str. 262–267).

Bolancé, C. G.-B. (2016). Predicting probability of customer churn in insurance. U *Modeling and Simulation in Engineering, Economics and Management* (str. 82–91). Springer.

Cheng, H.-Y. W.-C.-H.-L.-Y.-H.-H. (2020). Applying machine learning models with an ensemble approach for accurate real-time influenza forecasting in Taiwan: Development and validation study. *Journal of Medical Internet Research, 22*, str. e15394 https://doi.org/10.2196/15394.

Chintala, S. (2024). Smart BI systems: The role of AI in modern business. *ESP Journal of Engineering & Technology Advancements, 4(3), 4*, str. 45–58. doi:https://doi.org/10.56472/25832646/JETA-V4I3P05

Eboigbe, E. O. (2023). Business intelligence transformation through AI and data analytics. *Engineering Science & Technology Journal, 4(5)*, str. 285–307.

El-Sappagh, S. H. (2011). A proposed model for data warehouse ETL processes. *Journal of King Saud University - Computer and Information Sciences, 23(2), 23*, str. 91–104.

Emery, F. E. (1978). Characteristics of socio-technical systems. U *The emergence of a new paradigm of work.* Centre for Continuing Education, Australian National University.

Fayyaz, Z. E. (2020). Recommendation systems: Algorithms, challenges, metrics, and business opportunities. *Applied Sciences, 10*, str. 7748.

Ghasemaghaei, M. (2019). Does data analytics use improve firm decision making quality? The role of knowledge sharing and data analytics competency. *Decision Support Systems, 120*, str. 14-24.

Gorry, G. &.-M. (1971). A framework for management information systems. *Sloan Management Review, 13*.

Gupta, P. &. (2024). Unsupervised learning for real-time data anomaly detection: A comprehensive approach. *International Journal of Computer Science and Engineering, 11*, str. 1-11. doi:https://doi.org/10.14445/23488387/IJCSE-V11I10P101

Hairach, M. B. (2023). Anomaly detection in PV modules: A comparative study of DBSCAN, k-means, isolation forest, and LOF. *Proceedings of CiSt 2023*, (str. 135–139). doi:https://doi.org/10.1109/CiSt56084.2023.10409931

Hercegovine, F. z. (2025). *Zvanična statistika BiH.* Federalni zavod za statistiku Bosne i Hercegovine. Dohvaćeno iz http://www.statistika.ba/

Hossain, A. (2017). Customer segmentation using centroid based and density based clustering algorithms. *Proceedings of the EICT Conference*, (str. 1-6). doi:https://doi.org/10.1109/EICT.2017.8275249

Huber, F. P. (2022). The wealth of (Open Data) nations? Open government data, country-level institutions and entrepreneurial activity. *Industry and Innovation, 29*, str. 992-1023.

Humphreys, P. A.-W. (2013). *Decision support in organizational transformation.* Springer US.

IDDEEA. (2025). *Agency for Identification Documents, Records and Data Exchange.* Dohvaćeno iz https://www.iddeea.gov.ba/

Inmon, W. H. (2010). *DW 2.0: The architecture for the next generation of data warehousing.* Elsevier.

Janssen, M. C. (2012). Benefits, adoption barriers and myths of open data and open government. *Information Systems Management, 29*, str. 258-268. doi:https://doi.org/10.1080/10580530.2012.716740

Jetzek, T., Avital, M., & Bjorn-Andersen, N. (2014). Data-driven innovation through open government data. *Journal of Theoretical and Applied Electronic Commerce Research, 9*, str. 100–120. doi:https://doi.org/10.4067/S0718-18762014000200004

Kilanko, V. (2022). Turning point: Policymaking in the era of artificial intelligence, by D. M. West & J. R. Allen. Brookings Institution Press.

Kilanko, V. (2023). *The transformative potential of artificial intelligence in medical billing: A global perspective.*

Kitchin, R. (. (2014). *The data revolution: Big data, open data, data infrastructures and their consequences.* Sage.

Klepić, Z. A. (2020). *Menadžment.* Sveučilište u Mostaru.

Kongthanasuwan, T. S. (2023). Market analysis with business intelligence system for marketing planning. *Information, 14*, str. 116. doi:https://doi.org/10.3390/info14020116

Lambe, P. (2011). The unacknowledged parentage of knowledge management. *Journal of Knowledge Management, 15*, str. 175-197.

Liang, T. &. (2011). Introduction to the special issue: Social commerce—A research framework for

social commerce. *International Journal of Electronic Commerce, 16*, str. 5-14. doi:https://doi.org/10.2753/JEC1086-4415160201

Mandić, M. Š. (2018). Clique comparison and homophily detection in telecom social networks. *International Journal of Electrical and Computer Engineering Systems, 9*, str. 81-87.

Mungoli, N. (2023). *Adaptive feature fusion: Enhancing generalization in deep learning models.*

Ogunleye, J. O. (2023). Predictive data analysis using linear regression and random forest. U *Data Integrity and Data Governance.* IntechOpen. doi:https://doi.org/10.5772/intechopen.107818

Risko, E. F. (2016). Cognitive offloading. *Trends in Cognitive Sciences, 20*, str. 676–688. doi:https://doi.org/10.1016/j.tics.2016.07.002

Simon, H. A. (2013). *Administrative behavior: A study of decision-making processes in administrative organization* (4 izd.). Simon & Schuster.

Sprague, R. H. (1980). A framework for the development of decision support systems. *MIS Quarterly, 4*, str. 1-26. doi:https://doi.org/10.2307/248957

Sreemathy, J. e. (2021). Overview of ETL tools and Talend-data integration. *7th International Conference on Advanced Computing and Communication Systems*, (str. 1650–1654).

Statistic, F. B. (2025). *First release of registered road motor vehicles for 2024.* Dohvaćeno iz http://fzs.ba/index.php/publikacije/saopcenjapriopcenja/transport-i-komunikacije/

Statistics, F. B. (2025). *First release of registered road motor vehicles for 2024.* Federal Bureau of Statistics. Dohvaćeno iz http://fzs.ba/index.php/publikacije/saopcenjapriopcenja/transport-i-komunikacije/

Stodolsky, D. (1982). *Review of Steven L. Alter: Decision support systems: Current practice and continuing challenges.* Systems Research. doi:https://doi.org/10.1002/bs.3830270109

Syed, A. S.-S. (2021). IoT in smart cities: A survey of technologies, practices and challenges. *Smart Cities, 4*, str. 429–475.

Škobić, D. & Šego, A. (2023). Open government data in the service of business analysis – The case of insurance in BiH. *34th Meeting of Insurers and Reinsurers.*

Škobić, D. K. (2020). Machine learning algorithms in the profitability analysis of casco insurance. *Age, 1*, str. 18-30.

W. H., S. D. (2010). *DW 2.0: The architecture for the next generation of data wareho.* Elsevier.

Weerakkody, V. I. (2017). Open data and its usability: An empirical view from the citizen's perspective. *Information Systems Frontiers, 19*, str. 285-300.

Žigienė, G. R. (2022). Setting the grounds for the transition from business analytics to artificial intelligence in solving supply chain risk. *Sustainability, 14*. doi:https://doi.org/10.3390/su141911827