

Application of Business Analytics in Demand Planning: An Example from the Fast Food Industry

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Abstract. *This paper presents an integrated business analytics framework for demand planning in the fast-food industry by combining descriptive, predictive, and prescriptive analytics within a single decision-support system. The framework is validated through a case study of a fast-food restaurant in Serbia, where highly dynamic raw material demand requires accurate forecasting and efficient inventory management. Descriptive analytics identify significant correlations, trends, and seasonal patterns in the data. The obtained forecasts are incorporated into a linear optimization model to support procurement decisions, reduce inventory costs, and minimize raw material shortages. The findings demonstrate that integrating forecasting with inventory optimization enhances operational decision-making and provides a practical, data-driven approach to demand planning. The proposed framework offers both managerial value and a methodological contribution to the application of integrated business analytics in demand planning.*

Keywords: Business analytics, demand management, fast food industry, optimization.

1 Introduction

The fast-food industry operates in a dynamic environment characterized by fluctuating demand, short product life cycles, and perishable raw materials. Therefore, accurate demand planning is essential, as forecasting errors can lead to excess inventory, shortages, higher costs, and operational inefficiencies. Business analytics is increasingly used to support data-driven decision-making and improve demand and inventory management.

Business analytics combines descriptive, predictive, and prescriptive analytics to support managerial decision-making. Descriptive analytics facilitates the exploration of historical data and the

identification of patterns, trends, and seasonal effects. Predictive analytics applies statistical and forecasting techniques to estimate future demand, while prescriptive analytics uses optimization models to recommend the most appropriate decisions under defined operational constraints. Although these analytical approaches have been widely studied, previous research has predominantly focused on improving forecasting accuracy, with limited attention given to integrating forecasting results directly into procurement and inventory planning.

To address this research gap, this paper proposes an integrated decision-support framework that combines descriptive, predictive, and prescriptive analytics for demand planning in the fast-food industry. The framework links demand forecasting with inventory optimization, enabling managers to translate demand forecasts into procurement decisions while considering operational constraints.

The proposed framework is validated through a case study of Company X, a fast-food restaurant in Serbia, using historical consumption data for three key raw materials collected between 2019 and 2023. The study aims to examine how the integration of business analytics methods can improve demand planning, inventory management, and operational decision-making. The analysis is conducted in three stages. First, descriptive analytics is used to prepare and explore the data by identifying trends, seasonal patterns, and relationships among variables. Second, predictive analytics evaluates several forecasting models to identify the most accurate approach for demand prediction. Finally, prescriptive analytics integrates the selected forecasting model into a linear optimization model to determine optimal procurement decisions and support inventory planning.

The main contribution of this study is the development of a unified analytical framework that combines demand forecasting and inventory optimization within a single decision-support system. The proposed approach integrates descriptive, predictive, and prescriptive analytics to support

managerial decision-making and advance business analytics applications in demand planning.

2 Fast-Food Demand Planning

Demand management is the process of planning, forecasting, and directing demand for products and services while coordinating key business functions such as marketing, sales, and logistics. The goal is to meet customer needs while optimizing resource utilization, reducing costs, and increasing forecast accuracy. Of particular importance is the optimization of inventory to avoid surpluses and shortages (Farag, 2026).

The demand management process generally comprises five phases: data collection, demand forecasting, balancing supply and demand, demand shaping through pricing and promotional activities, and continuous performance monitoring. Contemporary challenges include forecast uncertainty, rapidly changing consumer behavior, supply chain disruptions, and limited integration of data across organizational functions (Ivanov & Dolgui, 2022; Wamba et al., 2023).

2.1 Specifics of the fast-food industry

The fast food industry continues to grow, fueled by busy lifestyles and a demand for speed (fortunebusinessinsights.com, 2025). However, this growth is accompanied by significant challenges related to managing perishable inventory, volatile demand, and rising operational costs.

The industry's key challenges include changing consumer preferences toward healthier and more sustainable food, labor shortages, rising operating costs, intense competition from fast-casual restaurants and online food delivery platforms, and increasing regulatory and environmental requirements. These trends require restaurant operators to continuously adapt their products, pricing strategies, and operational processes while improving forecasting accuracy and minimizing food waste (Kasavan et al., 2022; Alsuwaidi et al., 2022; Kwok, 2022).

3 Business Analytics and Its Role in Decision Making

Business analytics is the process of transforming data into actions through analysis and insight in the context of organizational decision-making and problem-solving (Liberatore & Luo, 2010). The authors divide it into several phases, and the most common division is: descriptive analytics, predictive analytics, and prescriptive analytics. Descriptive analytics interprets historical data and determines what happened. Predictive analytics should predict the

values of variables that are not under the control of the decision maker or are under his partial control, and which will affect the success of the business (Vujošević & Vujošević, 2014). Prescriptive analytics uses optimization, heuristic, and simulation methods for the best courses of action based on the data obtained in the previous two phases.

Today's business is shaped by rapid technological progress and unstable markets, which create complex conditions for decision-making. Organizations produce and store huge amounts of data, which often remain unused (Bumblauskas et al., 2017). Although organizations generate and store unprecedented volumes of data, a substantial proportion remains underutilized for decision-making, limiting the potential value that can be extracted from organizational data assets (Liu, et al., 2023). In this context, it has become important to use business analytics to integrate decision-making processes in order to gain a competitive advantage and a higher level of company performance (Oesterreich et al., 2022; Debeljević & Peovski, 2026). The development of concepts such as "big data" has further accelerated this need. The rapid expansion of large and connected data sets creates new opportunities for innovation and improving the quality of decisions (Dwivedi et al., 2017).

In addition to collecting data, companies face the challenge of how to extract useful insights from data and turn them into actions. The focus is increasingly shifting towards data-driven decision-making. Business analytics provides tools and methodologies to transform raw data into strategic insights, helping managers make effective decisions. Research shows that the use of various types of analytics can help organizations make more intelligent decisions and increase business value from those decisions (Hindle & Vidgen, 2018; Li et al., 2022).

3.1 Limitations and Challenges in Implementation

Despite the significant advantages of business analytics for informed decision-making, its practical application faces several limitations and challenges. One of the main problems lies in the data itself, which is often inconvenient to analyze due to its huge volume, variety of formats, and rapid creation (Jagadish et al., 2014). This leads to various technical challenges in storing and processing data (Jagadish et al., 2014). Data quality is also of great importance because data can be incomplete, inconsistent or inaccurate, which makes it difficult to draw reliable conclusions later (Liu et al., 2023). In addition to technical aspects, a major challenge is the organizational culture itself, as well as the human aspects in accepting analytics. A large number of organizations still do not have a mature culture of data-driven decision-making, so employees may be reluctant to trust analytics or may have difficulties in

understanding analytical tools (Silaban, 2022). There is also a problem of translating analytical results into business actions, where it is not always clear how metrics and reports obtained from analytics can be transformed into concrete strategic decisions (Berman & Israeli, 2022). This lack of clarity leads to the fact that valuable analysis findings are sometimes not implemented, but remain at the report level. Another challenge is the operationalization of analytics, i.e., the integration of analytical models and tools into existing business processes and decision-making systems. Studies have shown that many companies have difficulty truly realizing value from business analytics programs in real-world decision-making conditions (Silaban, 2022).

The combination of these factors results in most organizations still using only a small portion of the available data for decision-making, as previously mentioned (Liu et al., 2023). Overcoming limitations such as data quality, lack of trust in analytics, and lack of integration of analytics teams into business processes is a prerequisite for realizing the full potential of analytics in decision-making.

4 Empirical Study

This paper utilizes data from Company X for the period 2019-2023, which pertains to the demand for three key raw materials that have the greatest impact on the production process. To preserve anonymity, these raw materials are designated as A, B, and C. Company X operates within the fast-food industry and generates approximately 20 million dinars in average monthly net sales. The costs of purchasing raw materials and other production inputs account for between 30% and 35% of total sales revenue. The three raw materials under consideration represent the most significant inputs, with their share accounting for approximately 50% of total procurement costs. Raw materials A and B are ordered on a daily basis due to their short shelf lives, while raw material C is purchased every three to four days, resulting from high inventory turnover and limited storage capacity. Demand fluctuations are driven by various factors, including promotions, local events, weather conditions, and sporting activities.

4.1 Application of Descriptive Analytics

Table 1 shows the results of a descriptive analysis of the consumption of the observed raw materials, which provide a comprehensive picture of the level of consumption and its variability, as well as the stability and patterns of demand during the observed period.

Raw material A shows moderate variability in consumption with a slight positive skewness, which means that occasional months with higher consumption have increased the average. Raw material B has a higher level of average consumption

and more pronounced variability, with positive skewness and a flatter distribution. Raw material C has the lowest consumption and the most stable pattern, with values that are closest to a normal distribution and without extreme deviations.

Table 1. Results of descriptive analytics

Measure	Raw material A	Raw material B	Raw material C
Arithmetic Mean	18435.417	25618.033	555.359
Median	17631	25075.500	541.395
Standard deviation	2906.11	4980.308	108.111
Minimum	13753	18395	375.880
Maximum	26665	38933	851.990
Range	12912	20538	476.110
Asymmetry Coefficient	0.982	0.895	0.879
Coefficient flattening	1.108	0.604	0.823
95% confidence interval	±750.729	±1286.550	±27.928
Number of observations	60	60	60

Correlation analysis was conducted to examine the relationship between the observed variables. The results, obtained using the Pearson correlation coefficient and additionally confirmed by scatter plots with regression lines, indicate a high degree of interdependence between the variables.

The correlation coefficients between the observed raw materials range from 0.857 to 0.963, indicating strong positive linear relationships among all variables. Beginning with the lowest correlation, raw materials A and B show $r = 0.857$ ($R^2 = 0.734$), meaning about 73% of the variability in the demand for raw material B is explained by variations in A. Moving to a higher correlation, raw materials A and C present $r = 0.928$ ($R^2 = 0.862$), reflecting a pronounced common movement in their consumption, partly due to technological and process connections. Finally, the highest degree of correlation is seen between raw materials B and C ($r = 0.963$; $R^2 = 0.927$), indicating an almost proportional movement of these variables and a very high level of interdependence in their consumption.

4.2 Application of Predictive Analytics

This chapter presents the results of predictive time series analysis conducted on the demand for raw material A in Company X. The objective was to identify the forecasting model that provides the highest accuracy based on historical demand data. Table 2 summarizes the performance of the evaluated time series models using standard forecast accuracy indicators calculated on the validation dataset. These indicators enabled an objective comparison of model performance and the selection of the most suitable approach for future demand forecasting. The identified model was subsequently considered for practical application in demand planning and data-driven business decision-making.

The results of the conducted analysis indicate that there is no universally optimal time series model that would provide the best results for all observed raw materials. Instead, for each time series, a model was identified that, according to the selected evaluation criteria, achieves the highest level of forecast accuracy. Based on the findings, the models that showed the best performance according to the criterion of mean absolute percentage error (MAPE) for each raw material were applied in the continuation of the research. Specifically, for raw material A, the Holt method proved to be the most accurate, whereas for raw material B, the multiplicative Holt–Winters method demonstrated the highest forecasting accuracy. For raw material C, the damped multiplicative Holt–Winters method achieved the best results (Winters, 1960). Table 4 shows the forecasted consumption quantities for each raw material for 2024, obtained by applying the aforementioned models that stood out as the most efficient within the framework of the conducted analysis.

Table 2. Results of predictive analytics

Time series	Raw material A		Raw material B		Raw material C	
Criterion	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
Method	Naive method	Holt	Multiplicative Holt-Winters		Multiplicative Holt-Winters	Damped Multiplicative Holt-Winters
Error	2916.04	8.79	3254.35	8.01	72.00	7.74

The obtained forecasts for 2024 will be used as input parameters within the framework of prescriptive analytics, with the aim of optimizing orders and supporting decision-making in the process of demand planning and inventory management. In this way, the predictive results represent the basis for further modeling and defining optimal procurement strategies in Company X.

Table 3. Forecasted demand for raw materials in 2024

Month	Raw material A [pcs]	Raw material B [pcs]	Raw material C [L]
January	26542	29975	752.78
February	26844	30297	767.34
March	27146	30612	802.82
April	27448	30922	825.37
May	27750	31225	818.29
June	28052	31522	908.19
July	28354	31811	831.00
August	28656	32092	900.07
September	28958	32365	921.91
October	29260	32630	987.05
November	29562	32920	937.19
December	29864	33314	978.16

4.3 Application of Prescriptive Analytics

To ensure optimal procurement planning and inventory management in Company X, a linear optimization model was developed that incorporates forecasted demand, ordering costs, inventory holding costs, and operational constraints, aiming at minimizing total costs. The model applies inventory optimization and procurement planning principles under variable demand and limited resources, enabling a balance between inventory levels and maintenance costs, while maintaining continuity in production supply. The sets, parameters, and primary components of the model are defined below as the foundation for formulating the optimization problem:

- Time period (months): $t = 1, \dots, T$, where T represents the total number of months observed;
- Raw materials: $i \in \{A, B, C\}$;
- Decision variables: $x_{i,t}$ - quantity of ordered raw materials i in period t ;
- Forecasted demand: $\widehat{D}_{i,t}$ - estimated demand for raw material i in period t ;
- Ordering costs: $c_{i,t}^p$ - unit cost of ordering the i -th raw material in period t ;
- Inventory holding costs: $c_{i,t}^h$ - cost of holding one unit of the i -th raw material during period t ;
- Monthly procurement budget: B_t - available budget for procurement of all raw materials in period t ;
- Minimum inventory level: S_i - minimum initial inventory level for raw material i ;
- Maximum stock level index: $MaxCover_i$ - maximum allowed number of months of stock coverage for raw material i ;
- Inventory balance: $I_{i,t}$ - quantity of raw material inventory i at the beginning of period t , obtained through the formula: $I_{i,t} = I_{i,t-1} + x_{i,t} - \widehat{D}_{i,t}$.

Based on the described parameters, a mathematical model of total cost minimization was formulated. The formulation of the objective function and model constraints is as follows:

$$(\min) \sum_{t=1}^T \sum_{i \in \{A,B,C\}} (c_{i,t}^p * x_{i,t} + c_{i,t}^h * I_{i,t})$$

(s.t.)

$$I_{i,t} = I_{i,t-1} + x_{i,t} - \widehat{D}_{i,t} \quad (\forall i, t) \quad (1)$$

$$\sum_i c_{i,t}^p * x_{i,t} \leq B_t \quad (\forall t) \quad (2)$$

$$I_{i,t} \leq MaxCover_i * \widehat{D}_{i,t} \quad (\forall i, t) \quad (3)$$

$$I_{i,t} \geq S_i \quad (\forall i, t) \quad (4)$$

$$x_{i,t} \geq 0 \quad (\forall i, t) \quad (5)$$

$$x_{A,t} \in N, x_{B,t} \in N \quad (6)$$

The objective function minimizes the total cost of purchasing and holding inventory during the observation period. The first group of constraints ensures that the inventory for each raw material at the

end of month t must be equal to the inventory of that raw material at the end of the previous month, increased by the order for month t and decreased by the forecast demand for month t . Constraints (2) ensure that the total value of orders in month t must not exceed the available budget for that month. Constraints (3) limit the inventory according to the corresponding *MaxCover* factor for each raw material. The *MaxCover* factor was introduced due to the perishability of raw materials. Within this constraint, it ensures that the inventory cannot exceed a certain percentage of the monthly demand to prevent spoilage of the ingredients. Constraints (4) ensure that the inventory level at the end of the month for each raw material must be greater than the defined monthly safety stock level S_i . Finally, constraints (5) and (6) represent natural constraints and an integer condition for raw materials A and B, given that they are ordered in pieces.

In the initial model setup, appropriate values are given for the parameters of forecasted demand, unit costs, safety stock level, initial stock, and *MaxCover* factor for raw materials. Also, an appropriate budget is defined for each month. The currency used throughout the paper is the Serbian dinar (RSD).

For raw material A, the unit ordering costs are $c_{A,t}^p = 53$ RSD/piece, while the inventory holding costs are $c_{A,t}^h = 2.75$ RSD/piece. The initial inventory level $I_{A,0}$ is 10000 pieces, while the safety stock level $S_A = 2000$ pieces. The *MaxCover* factor for raw material A is 0.5. The forecasted quantities of raw material A by month were previously calculated using the Holt method and are shown in Table 4.

For raw material B, the unit ordering costs are $c_{B,t}^p = 48$ RSD/piece, while the inventory holding costs are $c_{B,t}^h = 2.40$ RSD/piece. The initial inventory level $I_{B,0}$ is 20000 pieces, while the safety stock level S_B is 2500 pieces. The *MaxCover* factor for raw material B is 0.5. Forecasted monthly quantities obtained using the multiplicative Holt-Winters method are presented in Table 4.

For raw material C, the unit ordering costs are $c_{C,t}^p = 250$ RSD/L, while the inventory holding costs are $c_{C,t}^h = 5$ RSD/L. The initial inventory level $I_{C,0}$ is 200L, while the safety stock level $S_C = 100$ L. The *MaxCover* factor for raw material C is significantly higher than for raw materials A and B due to its longer shelf life, and is 1.8. The forecasted quantities of raw material C per month were previously calculated using the damped multiplicative Holt-Winters method and are shown in Table 4.

The available budget for ordering raw materials A, B, and C is 3500000 RSD per month. The budget is determined based on the percentage share of the costs of these raw materials in relation to the company's total sales costs, as well as the share of total sales costs in the total monthly sales of Company X. The following chapter will present the results of applying

the solver to optimize the previously described model in Excel.

The model is implemented so that the variables are $x_{i,t}$, the target cell represents the total cost in 12 months, and the constraints entered into the solver include: inventory balances for each raw material and month, monthly budget, *MaxCover* and minimum inventory, non-negativity, with $x_{A,t} \in N, x_{B,t} \in N$. Simplex LP was chosen as the solver method. The results of applying the solver are presented below. First, Table 4 shows the obtained decision variables, i.e., the values of the quantities of raw materials A, B, and C that need to be ordered in 2024 for each month. The objective function was 37625237.5 RSD, of which procurement costs were 37480237.5 RSD, and inventory holding costs were 144000 RSD. The budget was not a limiting factor because monthly consumption was less than the budgeted 3.5 million RSD. Also, *MaxCover* constraints were not active since the ending inventory was consistently below the upper limits. Monthly consumption is consistently below the defined budget, which indicates that the budget is somewhat higher than necessary in the current business conditions.

Table 4. Solver results

Raw material A	Quantities by month	Raw material B	Quantities by month	Raw material C	Quantities by month
X _{A,1}	18542	X _{B,1}	12474	X _{C,1}	652.78
X _{A,2}	26844	X _{B,2}	30296	X _{C,2}	767.34
X _{A,3}	27146	X _{B,3}	30612	X _{C,3}	802.82
X _{A,4}	27448	X _{B,4}	30922	X _{C,4}	825.37
X _{A,5}	27750	X _{B,5}	31225	X _{C,5}	818.29
X _{A,6}	28052	X _{B,6}	31521	X _{C,6}	908.19
X _{A,7}	28354	X _{B,7}	31810	X _{C,7}	831.00
X _{A,8}	28656	X _{B,8}	32092	X _{C,8}	900.07
X _{A,9}	28958	X _{B,9}	32365	X _{C,9}	921.91
X _{A,10}	29260	X _{B,10}	32630	X _{C,10}	987.05
X _{A,11}	29562	X _{B,11}	32919	X _{C,11}	937.19
X _{A,12}	29863	X _{B,12}	33314	X _{C,12}	978.16

Based on the obtained results, a clearly defined pattern of the optimal solution can be observed. Given that the budget constraints are not strict, and the purchase prices are constant, the optimal policy identified by the solver boils down to the Just-in-Time approach to inventory management. Within this approach, the initial month (January) is characterized by the use of existing stocks, while from February onwards, quantities corresponding to the forecasted demand are ordered, while maintaining a defined minimum level of safety stocks. In this way, continuity in supply is ensured while minimizing inventory holding costs and efficiently using system resources.

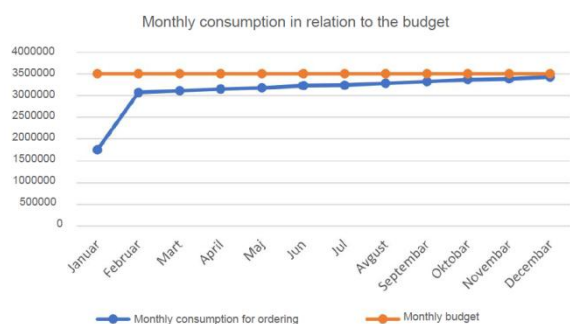


Figure 1. Monthly consumption compared to budget

Fig. 1 shows a comparative overview of actual consumption and available budget by month in the observed period. Based on the visual display, it is possible to see to what extent the realized consumption fits into the planned financial framework, as well as whether there are deviations in individual months.

In the observed period, consumption is below the budget limit, which indicates efficient cost management and stable procurement planning. This display allows management to clearly identify critical points in consumption, monitor financial discipline, and make timely decisions to optimize the budget and control costs.

5 Managerial and Theoretical Implications

The proposed framework provides practical support for managers operating in the fast-food industry by integrating demand forecasting with inventory optimization into a unified decision-support system. The results demonstrate that more accurate demand forecasts enable managers to reduce raw material shortages while avoiding excessive inventories of perishable products. By optimizing procurement decisions, the framework contributes to lower inventory holding costs, improved procurement timing, and more efficient allocation of financial resources.

Furthermore, the use of quantitative forecasting and optimization techniques supports data-driven decision-making, reducing reliance on managerial intuition. Since the framework is based on widely available analytical tools and standard forecasting methods, it can be readily adapted to other restaurants and small- and medium-sized enterprises (SMEs) facing similar demand planning challenges.

This study contributes to the business analytics literature by demonstrating the integration of descriptive, predictive, and prescriptive analytics within a single demand planning framework. Unlike previous studies that primarily focus on forecasting accuracy, the proposed approach establishes a direct

connection between demand forecasting and inventory optimization, thereby extending the application of business analytics in operational decision-making.

The research also provides a methodological example of combining time-series forecasting with linear programming in a real business setting.

6 Discussion and conclusion

The results demonstrate that the proposed business analytics framework provides an effective approach to demand planning in the fast-food industry by integrating descriptive, predictive, and prescriptive analytics within a single decision-support system. Descriptive analysis identified clear trends and seasonal patterns in the consumption of key raw materials, providing a reliable basis for subsequent forecasting and optimization. Among the evaluated forecasting techniques, the Holt and Holt–Winters models achieved the highest forecasting accuracy, confirming their suitability for demand characterized by both trend and seasonality. The integration of these forecasts into a linear programming model enabled the optimization of procurement decisions while considering budgetary and storage constraints. Furthermore, scenario analysis confirmed that the proposed model remains robust under changes in key planning parameters, highlighting its practical applicability in dynamic business environments.

From a managerial perspective, the framework supports more efficient procurement planning by reducing the risk of raw material shortages and excessive inventories, thereby lowering inventory-related costs and improving resource utilization. By combining forecasting with optimization, the proposed approach enables managers to make data-driven procurement decisions rather than relying primarily on experience or intuition. Moreover, because the framework is based on widely available analytical methods and software tools, it can be readily adapted to other restaurants and small- and medium-sized enterprises operating under similar demand conditions.

From a theoretical perspective, this study extends the application of business analytics by demonstrating how descriptive, predictive, and prescriptive analytics can be integrated into a unified framework for operational decision-making. Unlike approaches that focus solely on forecasting performance, the proposed methodology establishes a direct connection between demand forecasting and inventory optimization, providing a practical example of integrating forecasting models with mathematical optimization in a real business context.

The study has several limitations. The analysis is based on a single case study and considers only three key raw materials, which may limit the generalizability of the findings. In addition,

forecasting accuracy depends on the quality and availability of historical data, while unexpected market changes, supply chain disruptions, and operational constraints may affect the practical implementation of the proposed model. A further limitation is that a substantial portion of the historical dataset corresponds to the COVID-19 period, during which consumer behavior and demand patterns differed from normal market conditions. Therefore, the forecasting models may partially capture extraordinary fluctuations that are not fully representative of post-pandemic demand patterns. However, the inclusion of 2023 as the validation period partially mitigates this limitation by evaluating model performance under more stable business conditions.

Future research could extend the framework by incorporating a larger number of products, additional operational constraints, and external demand drivers such as weather conditions, promotional activities, or economic indicators. Furthermore, the application of advanced machine learning techniques and multi-objective optimization models may further improve forecasting performance and procurement planning in complex supply chain environments.

References

- Alsuwaidi, M., Eid, R., & Agag, G. (2022). Tackling the complexity of guests' food waste reduction behaviour in the hospitality industry. *Tourism Management Perspectives*, 42. doi:10.1016/j.tmp.2022.100963
- Berman, R., & Israeli, A. (2022). The value of descriptive analytics: Evidence from online retailers. *Marketing Science, INFORMS*, 41(6), 1074–1096. doi:10.1287/mksc.2022.1352
- Bumblauskas, D., Nold, H., Bumblauskas, P., & Igou, A. (2017). Big data analytics: Transforming data to action. *Business Process Management Journal*, 23(3), 703–720. doi:10.1108/BPMJ-03-2016-0056
- Debeljević, S., & Peovski, F. (2026). Business Analytics for Ride-Hailing Platforms: Demand Forecasting and Ride-Completion Modeling. *Applied Decision Analytics*, 2(1), 283–294. https://doi.org/10.66972/ada21202625
- Dwivedi, Y. K., Janssen, M., Slade, E. L., Rana, N. P., Weerakkody, V., Millard, J., & Snijders, D. (2017). Driving innovation through big open linked data (BOLD): Exploring antecedents using interpretive structural modeling. *Information Systems Frontiers*, 19(2), 197–212. doi:10.1007/s10796-016-9675-5
- Farag, M. I. H. (2026). Bridging Prediction and Prescription: Explainable AI for Managerial Decision Analytics under Uncertainty. *Applied Decision Analytics*, 2(1), 295–319. https://doi.org/10.66972/ada21202626
- Fortune Business Insights. (2025). Fast food market size, industry share & COVID-19 impact analysis. Retrieved from https://www.fortunebusinessinsights.com/fast-food-market-106482
- Hindle, G. A., & Vidgen, R. (2018). Developing a business analytics methodology: A case study in the food bank sector. *European Journal of Operational Research*, 268(3), 836–851. doi:10.1016/j.ejor.2017.06.031
- Ivanov, D., & Dolgui, A. (2022). The shortage economy and its implications for supply chain and operations management. *International Journal of Production Research*, 60(24), 7141–7154. doi:10.1080/00207543.2022.2118889
- Jagadish, H. V., Gehrke, J., Labrinidis, A., Papakonstantinou, Y., Patel, J. M., Ramakrishnan, R., & Shahabi, C. (2014). Big data and its technical challenges. *Communications of the ACM*, 57(7), 86–94. doi:10.1145/2611567
- Kasavan, S., Siron, R., Yusoff, S., & Fakri, M. F. R. (2022). Drivers of food waste generation and best practice towards sustainable food waste management in the hotel sector: A systematic review. *Environmental Science and Pollution Research*, 29, 48152–48167. doi:10.1007/s11356-022-19984-4
- Kwok, L. (2022). Labor shortage: A critical reflection and a call for industry-academia collaboration. *International Journal of Contemporary Hospitality Management*, 34(11), 3929–3943. doi:org/10.1108/IJCHM-01-2022-0103
- Li, Lei & Lin, Jiabao & Ouyang, Ye & Luo, Xin (Robert). (2022). Evaluating the impact of big data analytics usage on the decision-making quality of organizations. *Technological Forecasting and Social Change*. Elsevier, 175(C). doi:10.1016/j.techfore.2021.121355
- Liberatore, M. J., & Luo, W. (2010). The analytics movement: Implications for operations research. *Interfaces*, 40(4), 313–324. doi:10.1287/inte.1100.0502
- Liu, S., Liu, O., & Chen, J. (2023). A Review on Business Analytics: Definitions, Techniques, Applications and Challenges. *Mathematics*, 11(4), 899. doi.org/10.3390/math11040899
- Silaban (2022). Challenges in Business Analytics Implementation: A Comprehensive Review Using TOE Framework. Milestone. *Journal of Strategic Management*, 2(2). doi:org/10.19166/ms.v2i2.5953

- Vujošević, M., & Vujošević, D. (2014). Business analytics: A challenge to managers, researchers and software engineers. *Info M*, 13(50), 4–14.
- Wamba, S. F., Queiroz, M. M., & Trinchera, L. (2020). Dynamics between Blockchain Adoption Determinants and Supply Chain Performance: An Empirical Investigation. *International Journal of Production Economics*, 229(2). doi:org/10.1016/j.ijpe.2020.107791
- Winters, P. R. (1960). Forecasting sales by exponentially weighted moving averages. *Management Science*, 6(3), 324–342. <https://doi.org/10.1287/mnsc.6.3.324>