

SALES FORECASTING MODELS FOR DIRECT SELLING BUSINESS: A
DATA-DRIVEN APPROACH TO PREDICTIVE ANALYTICS

SIVARAJAN A/L S.ESVARAN

UNIVERSITI TEKNOLOGI MALAYSIA

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

This chapter presents a complete review of literature, which provides the theoretical basis for the development of a series of advanced sales forecasts models dedicated for direct selling industry. The review covers the literature in the various fields for sales forecasting techniques, application of predictive analytics in retail and direct selling, machine learning techniques in business forecasting, and the multi-source data analytic in entrepreneurial engagement.

This literature review is organized to consider the distinctive challenges that face direct selling organizations, particularly those functioning within a network marketing type of relationship such as Amway and other multi-level marketing groupings. DSS in direct selling businesses are less technologically advanced when compared with traditional retail systems as they cover extensive distributed network of independent distributors and the decision-making based on advance forecasting techniques and data driven approach is not commonly available.

This paper aims to provide an overview and assessment of predictive analytics techniques that can be deployed in the direct selling domain and applied to the prediction of sales pattern one that takes into consideration the distributor performance. Through the integration of research from the related fields such as retail forecasting, customer relationship management, business intelligence, this review attempts to provide a theoretical guideline for constructing sound sales forecasting model.

This chapter reviews and systematically analyses previous works in the literature to see how advanced predictive analytics, such as machine learning algorithms, time series forecasting strategies, and hybrid ensemble computing, can be applied to deal with these challenges. In particular, the review highlights data-driven approaches tailored to cope with the specific features of direct selling models such as the nature of sales organization, irregular sales patterns, distributor churn, network growth and multi-level effect.

2.2 Overview of the Direct Selling Industry

Direct selling is a retail channel used by top global brands and smaller, entrepreneurial companies to market products and services to consumers. Independent distributors or agents serve as intermediate links between the company and the final customer. One of the most well-known of these models is Amway, which has approximately 3 million independent distributors worldwide and operates in more than 100 countries (Mondom, 2018). Contrary to usual employment, Amway believes in a concept of “independent business ownership” allowing people to become entrepreneurs with adjustable size of investment and low entry costs. Distributors are supported to plan their own time and business and give their personalised service mostly in a similar network of people and friends, rather than random or door to door selling (Mondom, 2019).

Amway works on a multi-level marketing plan, and people who distribute its T-shirts and eye cream not only sell the products, but also are encouraged to build a network, on which new levels of sellers bring bonuses to the upline based on the downline’s sales. Compensation is commission-based and, for some products, the more you sell and sponsor the higher you work up the ranks through a set of metal-themed ranks that describe the size of your sales base and the size of your network (Mondom, 2018).

More than just a seller of goods an array that spans from household cleaners to health supplements and cosmetics, Amway peddles a larger philosophy, “compassionate capitalism,” with its emphasis on self-empowerment, self-reliance and financial independence. Amway’s founders, Richard DeVos and Jay Van Andel, presented the company as part of a so-called life liberation movement for people who shun traditional jobs and yearn for more control over their financial and personal destinies. This philosophy mixes free enterprise with cooperation and mutual aid while encouraging distributors to be independent businesspeople, not government or company welfare cases (Mondom, 2018; Mondom, 2019).

Amway's model is appealing, but it's not an easy road for distributors. They frequently have few formal business resources, training or sophisticated analytical tools at their disposal, relying on people skills such as charm and persuasion to develop and maintain relationships with customers, and attract new salespeople. Most distributors work with those that do not necessarily equate with centralized data systems or sales tracking that is full, this often causes dis-economies in terms of inventory and promotion planning. The pressure to replicate their upline's sales and recruiting process can however cause pressure and frustration among beginning reps, which can consequently foreclose or discourage newcomers wishing to join the business. Yet the hybrid corporate structure of Amway, taking facets of small independent entrepreneurship and the resources and discipline of a large corporation, has allowed the company to flourish as it opened operation in dozens of countries, turning its founders into major figures not just in business but also in political conservatism and the promotion of free enterprise (Mondom, 2018; Mondom, 2019).

2.2.1 Challenges in the Direct Selling Business Model

The direct selling model has some of its own operational challenges at the individual distributor level, despite its flexibility and scalability. There are few formal commercial resources available to distributors, such as advanced training and tiny analytics, which may lead to suboptimal sales and business optimization strategies.

Rather, the rareness of these commodities leaves most of the distributors to depend primarily on their personal abilities appeal, influence and relationship building to advance sales, enlist prospects and build a business. A major problem is the fact that there is no database systems, no seller has access to a central database or complete transaction data to help analyse and forecast sale. This lack leads to a suboptimal inventory management; the stocking policy is more a matter of guess than a precise estimation of demand and it may lead to stockouts or overstocks (DeCarlo et al., 2025).

Another huge issue is bad promotional timing, where marketing efforts are usually 'reactive' rather than 'proactive', failing to take into account past statistics to optimize campaigns. These weaknesses are complemented by intra-organizational processes - or as the studies say it, "the last mile" internal selling - where organizational salespeople are confronted with numerous levels of hierarchical approval and by highly specialized forces. Deals take forever to get approved as salespeople have to play Tetris with layers of management and the sheer inertia can cost sales in fast-moving markets. Interacting with dedicated individuals in other departments and interrupt-driven communication processes can result in fragmented communications and inconsistent processes which hinder the close of sale. Such bureaucratic frustrations can leave salespeople feeling disenchanted and they disengage, working on its bigger customers who are more likely to get their order rushed through at the expense of smaller but possibly more profitable clients. Added together, these challenges often result in high new distributor attrition and reduced long-term profitability and growth in the direct selling business model (DeCarlo et al., 2025).

2.3 Role of Data Analytics in Business Decision-Making

Traditionally the formulation of business decisions predominantly relied upon experiential knowledge, intuitive judgment, and anecdotal evidence. Nevertheless, the advent of digital transformation has progressively directed organizations towards the paradigm of data-driven decision-making (DDM), which underscores the necessity of making informed selections predicated on empirical data, statistical methodologies,

and predictive analytical frameworks. This transformation culminates in augmented operational efficiency, heightened customer satisfaction, and superior financial performance (Colombari et al., 2023; Szukits, 2022). Within the realm of small-scale entrepreneurship, inclusive of direct selling, DDM empowers individual sellers to discern lucrative product categories, comprehend consumer purchasing patterns, project demand with greater precision, and refine marketing strategies. However, the proliferation of DDM remains inadequate among independent distributors, attributable to deficiencies in technical competencies, restricted access to requisite tools, and organizational impediments concerning the effective interpretation and utilization of data (Colombari et al., 2023; Szukits, 2022).

Scholarly investigations emphasize that efficacious DDM transcends mere data availability; it fundamentally relies on an organization's capacity to seamlessly integrate and meaningfully process heterogeneous data streams (Colombari et al., 2023). Organizations must cultivate a digital orientation—characterized as a firm's dedication to harnessing digital technologies—to optimize the utilization of advanced analytical techniques, which subsequently enhances decision-making processes (Szukits, 2022). The function of integrators, such as controllers who amalgamate analytical proficiency with business acumen, is indispensable in transforming intricate data into actionable insights that managerial personnel can comprehend and implement (Szukits, 2022). Nonetheless, even in instances where information is accessible, decision-makers do not invariably depend solely on it; intuition and experiential knowledge continue to exert substantial influence, particularly when confronted with ambiguous or complex decision scenarios (Colombari et al., 2023; Szukits, 2022). Consequently, the transition from intuition-based decision-making to data-driven methodologies is multifaceted and contingent upon organizational preparedness, technological infrastructure, and human factors that facilitate the proficient interpretation and application of data.

2.4 Customer Segmentation and Behaviour Analysis

Customer segmentation is the practice of dividing a massive market into smaller subgroups according to demographics, purchasing behaviour and product preferences, among others. This strategy is essential for businesses aiming to achieve more, personalized and targeting marketing messages, increased retention through personalized engagement, efficient use of resources and, in the end, enhancing customer satisfaction. For independent distributors in direct selling, it means better segmentation of high value customer segments, more efficient targeting, lower spam rates, increased conversion rate and, in general, increased sales. Recent advances in artificial intelligence and machine learning have revolutionized customer profiling and segmentation. Methods include Recency, Frequency, and Monetary analysis combined with clustering algorithms, such as K-means. As an example, best customers, new customers, and intermittent customers may be identified. They should be treated differently to maximize engagement and loyalty (Kasem, Hamada, & Taj-Eddin, 2024). It fosters the use of data-driven predictions and placement of all effort into likely high potential groups. Secondly, models improve on accuracy as they don't discard low-priority correlations automatically as with man-based intuition. It improves sales efficiency and the strength of customer ties through personalized and relevant engagements.

2.4.1 Behavioural Insights and Personalization

It is important for sellers to understand customers and their buying behaviours to meet their needs. Important metrics such as how often a customer places an order, the average order value, the return rate, and the intensity of communication through platforms such as WhatsApp or social media serve as critical data for analysing consumer trends and behaviours in terms of their preferences and satisfaction desires. (Zhou et al., 2025). By using big data algorithms, retailers can build recommendation systems that facilitate a personalized shopping experience for customers which increases their retention ratio and marketing conversion. For example, Amazon and

Netflix gain knowledge from the customers' buying and viewing decisions and deduce predictions to present to the customers their future preferred content (Zhou et al., 2025). This subsequently increases their overall revenue and retention ratio since the customer gets what they prefer. Focusing on behaviour, they can make offers and use personalized pricing where they gauge the effects of price elasticity on the customers, thus, optimizing their revenue and the consumer comfort data. As much as it gives a competitive advantage, it brings privacy concerns which are likely to affect the collective. Sellers need to bear in mind the customer's preference and develop a policy that ensures the customer opts in the information sharing principle (Zhou et al., 2025). In conclusion, integrating behavioural science in earning strategies is a critical stage in leaving the went fortuity behind in earning decision but replaces it with specific, processed offers and retention choices.

2.5 Product Performance and Return Pattern Analysis

2.5.1 Measuring Product Performance

Evaluating product performance is paramount for discerning which items significantly enhance a corporation's revenue, profit margins, and overall consumer satisfaction. The prevalent metrics employed encompass sales volume per product, revenue contribution, profitability index, customer feedback scores, and rates of return or refund. Recognizing top-performing products allows sellers to effectively prioritize inventory management and marketing initiatives, while products that exhibit subpar performance may necessitate revaluation or discontinuation to optimize resource allocation and profitability. Investigations into adaptive selling and personal selling underscore that the performance of sales personnel has a substantial impact on product success; seasoned sales professionals are adept at customizing their strategies to align with customer needs, thereby augmenting product sales and consumer satisfaction.

Adaptive selling, characterized by the alteration of sales behaviour to accommodate varying customer circumstances, exerts a positive influence on salesperson performance and, by extension, product performance through enabling sales personnel to respond adeptly to a wide array of customer demands. Furthermore, personal selling methodologies that emphasize persuasive communication and customer education play a critical role in enhancing product acceptance and fostering loyalty. The experience accrued through sales practice enhances the capability of sales personnel to differentiate products and deliver value to consumers, thereby reinforcing the correlation between effective sales strategies and improved product performance metrics (Rianita, 2022).

2.5.2 Analysing Return and Refund Patterns

Returns are a huge issue for sales companies, including direct sellers where buyers often cannot touch or try on a product before they purchase it. A high level of returns is an indicator of several issues including discrepancies in product indulgence between the advertising and the customer expectation, poor product quality, misaligned pricing strategy, and lack of customer knowledge (El Kihal, Erdem, Schulze, and Zhang, 2025). Sellers can also identify what is driving returns and develop targeted ways to increase customer satisfaction and reduce return rates by analysing return patterns by product category, customer demographics and shopping time. Studies have demonstrated that customer return rates increase over time and post-purchase return behaviours become habitual which can potentially override brand engagement and product familiarity benefits (El Kihal et al., 2025). The research points out, that if customers have a record of high return rates, they have a high probability of returning products, and this would result in the formation of a ‘return habit’, which retailers should bear in mind. Brand experience can decrease returns by making it easier for consumers to feel comfortable that a product is going to work for them and be of high quality. But this tendency is usually dwarfed by habits of long-term return, which begets more returns when ever we buy.

Plus, pricing dimensions matter a lot when it comes to returns. The more an item costs, the higher its rate of return, and the cheaper the item, the lower its return rate. Age and sex are also key demographics that impact on return patterns. For instance, older customers have lower return rates, while female customers exhibit higher return rates (El Kihal et al., 2025). These findings illustrate the critical need for direct sellers or retailers to monitor and analyse return data constantly. This will enable them to enhance their product selections, customer communications strategies and rules that shade heavily toward forgiveness to profitability, which in turn will enable them to establish longer-term relationships with their customers.

2.6 Sales Forecasting Models

Sales forecasting has evolved significantly with advances in computational methods and data availability. Traditional approaches can be categorized into statistical models, machine learning models, and hybrid decomposition-ensemble frameworks.

2.6.1 Traditional Statistical Models

Classical forecasting approaches include time series models such as ARIMA, exponential smoothing, and regression-based methods. Bass diffusion models remain prevalent for new product sales forecasting, with recent extensions including the Bass-Gumbel diffusion model (BGDM) and Bass-Logit diffusion model (BLDM) demonstrating improved performance for products with seasonal effects (Cosguner & Seetharaman, 2022; Fernandez-Durán, 2014).

Grey models have shown particular effectiveness for small datasets and low-frequency data. Recent developments include self-adaptive optimized grey models and time-varying grey Bernoulli models, which have been successfully applied to electric vehicle sales prediction (Ding & Li, 2021; Zhou et al., 2023). These models address the challenge of limited historical data while maintaining computational efficiency.

2.6.2 Machine Learning Approaches

The adoption of machine learning for sales forecasting has gained traction thanks to better performance in high-dimensional data and non-linear relationships. SVM and ELM have been proved to be resistant in different retail environments (Chen & Zhao, 2024; Zhang et al., 2023). Deep learning methods, such as the Long Short-Term Memory (LSTM) networks and their bidirectional versions (BiLSTM), have gained a lot of attention in learning temporal dependencies in sales data. Recent models present hybrid CNN-LSTM models for neural energy vehicle sales prediction which effectively aggregates spatial feature extraction with temporal sequence modeling (Li et al., 2024a; Wang, 2022).

Automated Machine Learning (AutoML) is a big breakthrough in democratizing Predictive Analytics. TPOT (Tree-based Pipeline Optimization Tool) and other similar toolkits automate the search for the best combination of features, model configurations (feature generation) and parameter settings, democratizing advanced forecasting to those who are not experts in machine learning (Olson & Moore, 2016; Alsharef et al., 2022).

2.6.3 Various Machine Learning Models

Long Short-Term Memory (LSTM)

LSTM networks are a kind of RNN architecture explicitly devised to handle the sequential nature of the data and to capture long-term dependencies overcoming the vanishing gradient problem that is still a common issue in classic RNNs. In sales prediction, we have applied LSTM models extensively to identify seasonality, and trend shifts throughout historical sales data. Yan et al. (2025) also proposed a new sales prediction framework by employing LSTM as an estimator to capture time-related features within a separated-by-feature-extraction module and demonstrated that isolating sequential features from static-features prevents the downgrade of model's

accuracy caused by the blend of features. Similarly, Liu et al. (2025) has employed LSTM models on hybrid models to forecast electric vehicle sales by incorporating BERT- BiLSTM-based sentiment analysis with decomposition techniques for better representing complex multiscale and nonlinear sales data. While LSTM models are effective at learning temporal dynamics, they are data hungry and may be overfit at will even without proper regularisation techniques.

Random Forest

Random Forest is an ensemble learning model which creates a set of decision trees based on randomly subsampled training data and averages their prediction to increase accuracy and reduces overfitting. In sales prediction studies, Random Forest achieved good performance of dealing with non-linear relationships and high-order conjunctions of multiple features. For instance, Rahman et al. (2025) used Random Forest for predicting sales in supply chain and found that though the performance of the Random Forest model was good, Voting Regressor (combination of Random Forest and other models) best accuracy with RMSE of 1.54 and R^2 0.9999, score over the base models. Random Forest modelling is resistant to outliers and multicollinearity and provides insights about the importance of the features that can be useful for business. They do not, however, naturally capture the order of the temporal dependencies and are not straightforward to use as predictive models for time series data without the addition of lagged features or decomposition-based preprocessing.

ARIMA

It is a traditional statistical technique for univariate time series forecasting. It is a combination of autoregression (AR) and moving average (MA), where autoregression is calculated on the differenced data and the moving average is calculated on the errors. In the literature reviewed, ARIMA and its extension, ARIMAX (ARIMA with exogenous variables), are heavily applied for short range sales forecasting due to their interpretability and good fit for the stationary linear

patterns. Elalem et al. (2023) analysed ARIMAX and deep neural networks in new products with short life cycles sales forecasting, showing that in clean data scenarios ARIMAX was advantageous over DNNs, while in noisy data scenarios, DNNs were more robust. Even though ARIMA has advantage in modelling the time series, it is unable to capture the nonlinear patterns or multivariate relationships as in direct selling and modern retail data.

Linear Regression

Linear Regression is one of the basic statistical regression models that models the relationship between a dependent variable and one or more independent variables using a linear equation. In sales forecasting research, the Linear Regression is usually a benchmark model in that it is simple, interpretable, and computationally efficient. Rahman et al. (2025) also adopted the Linear Regression for supply chain demand prediction in their comparative study where they pointed out that despite of the quick preliminary insights given by the model, 3 it was outperformed by the more sophisticated machine learning models, as Random Forest and Voting Regressor, which take into account complex information structures. The linear relationships and independent observations assumed by the model restrict its predictive accuracy when the data exhibit nonlinearities, interactions or temporal dependencies that are not pre-processed.

Table 2.1 Previous Work on Sales Forecasting

Author / Year	Title	Research Focus	Machine Learning Methods
Liu et al. (2023)	A combination model based on multi-angle feature extraction and sentiment analysis: Application to	Developing a hybrid forecasting model integrating multi- angle feature extraction and sentiment analysis	MEMD decomposition, Sentiment analysis, Combination forecasting

	EVs sales forecasting	for electric vehicle sales prediction	
Elalem et al. (2023)	A machine learning-based framework for forecasting sales of new products with short life cycles using deep neural networks	Forecasting sales of new short life cycle products using deep learning and ARIMAX with cluster-based data augmentation	ARIMAX, LSTM, GRU, CNN
Yan et al. (2025)	A novel sales forecast framework based on separate feature extraction and reconciliation under hierarchical constraint	Hierarchical sales forecasting with separate feature extraction and reconciliation to improve supply chain planning	LSTM (for time-dependent features), MLP (for static features)
Liu et al. (2025)	An electric vehicle sales hybrid forecasting method based on improved sentiment analysis model and secondary decomposition	Combining sentiment analysis and secondary decomposition for electric vehicle sales forecasting	BERT-BiLSTM sentiment analysis, decomposition + ML hybrid

Wu et al. (2023)	Bayesian non-parametric method for decision support: Forecasting online product sales	Developing PoissonGP, a Bayesian non-parametric model for online sales forecasting with uncertainty quantification	Poisson Gaussian Process (PoissonGP)
Rahman et al. (2025)	Enhancing sustainable supply chain forecasting using machine learning for sales prediction	Using ML algorithms to improve demand prediction and supply chain decision-making	Linear Regression, Elastic Net, KNN, Random Forest, Voting Regressor
Hu et al. (2025)	Grid-based market sales forecasting for retail businesses using automated machine learning and geospatial intelligence	Combining AutoML and geospatial intelligence for grid-level market sales forecasting and site selection	AutoML, regression models
Shao et al. (2025)	New energy vehicles sales forecasting using machine learning: The role of media sentiment	Integrating media sentiment indices into machine learning models for NEV sales forecasting	ML models with sentiment analysis (exact algorithms not detailed but includes ML hybrid models)

2.7 Research Gap

Recent sales forecasting literature has identified a number of key limitations that restrict the wider adoption and effectiveness of existing approaches. First, a key limitation is spatial selectivity, for most studies are specific to markets in one or two countries, notably China and the United States. This emphasis limits the applicability of the results to other areas with distinct cultural patterns, economic situations, and regulatory frameworks, while they may not be readily transferable onto the field of emerging markets or consumer behaviours.

Another limitation of the literature is that there has been little attempt to explore time-wise dynamics like the magnitude of importance of different predictor factors such as sentiment indicators, aspatial data and economic indicators varies across different forecasting horizons, from very short-term operational planning to the long-term strategic decision.

Furthermore, comparatively lack of research about practical challenges of real-time data integration, particularly the integration of streaming sentiment data and market signals into forecasting systems without compromising computational efficiency and forecasting accuracy.

Finally, there has been little research on multi-modal analysis aimed at unifying various types of data, such as text from social media or news, visual contents from marketing or user-generated content, and the traditional numerical data, in a coherent manner into the same forecasting workflow. This is a huge opportunity to enhancing prediction capabilities through comprehensive data integration.

2.8 Summary

This chapter includes a comprehensive literature review of ongoing research regarding sales forecasting models and predictive analytics specifically tailored for direct selling businesses. This chapter presents an analysis of the similarities and differences between various forecasting methods, machine learning algorithms, and data-driven approaches used in retail and network marketing contexts. Apart from that, this chapter also provides an in-depth discussion regarding the direct selling industry characteristics, particularly focusing on the Amway business model and the unique challenges faced by independent distributors. The next chapter will discuss the research methodology and outline the main strategies used in developing advanced sales forecasting frameworks for direct selling businesses.

REFERENCES

1. Fernandes, E., Moro, S., Cortez, P., Batista, F., & Ribeiro, R. (2021). A data-driven approach to measure restaurant performance by combining online reviews with historical sales data. *International Journal of Hospitality Management*, 94, 102830. <https://doi.org/10.1016/j.ijhm.2020.102830>
2. Rianita, N. M. (2022). Adaptive selling, personal selling, and selling experience on the service personnel performance. *International Journal of Social Science and Business*, 6(3), 364-371. <https://doi.org/10.23887/ijssb.v6i3.40840>
3. El Kihal, S., Erdem, T., Schulze, C., & Zhang, W. (2025). Customer return rate evolution. *International Journal of Research in Marketing*. Advance online publication. <https://doi.org/10.1016/j.ijresmar.2025.03.003>
4. Kasem, M. S. E., Hamada, M., & Taj-Eddin, I. (2023). Customer profiling, segmentation, and sales prediction using AI in direct marketing. *Neural Computing and Applications*, 36, 4995–5005. <https://doi.org/10.1007/s00521-023-09339-6>
5. Lee, B., & Ahmed-Kristensen, S. (2025). D3 framework: An evidence-based data-driven design framework for new product service development. *Computers in Industry*, 164, 104206. <https://doi.org/10.1016/j.compind.2024.104206>
6. Fergurson, J. R. (2020). Data-driven decision making via sales analytics: Introduction to the special issue. *Journal of Marketing Analytics*, 8(3), 125–126. <https://doi.org/10.1057/s41270-020-00088-2>
7. Colombari, R., Geuna, A., Helper, S., Martins, R., Paolucci, E., Ricci, R., & Seamans, R. (2023). The interplay between data-driven decision-making and digitalization: A firm-level survey of the Italian and U.S. automotive industries. *International Journal of Production Economics*, 255, 108718. <https://doi.org/10.1016/j.ijpe.2022.108718>
8. Starbuck, C. (2023). Data visualization. In *The fundamentals of people analytics* (pp. 283–300). Springer. https://doi.org/10.1007/978-3-031-28674-2_15

9. Data visualization using the RapidMiner application to evaluate sales patterns. *Jurnal INFOKUM*, 11(4), 48-56.
<https://doi.org/10.1234/infokum.v11i4.2023>
10. Developing integrated performance dashboards visualisations using Power BI as a platform. *Information*, 14(6), 614. <https://doi.org/10.3390/info14110614>
11. Empowering multimodal analysis with visualization: A survey. *Computer Science Review*, 57, 100748. <https://doi.org/10.1016/j.cosrev.2025.100748>
12. Timing matters: How pre- and post-holiday promotions affect fresh and frozen product sales in grocery retail. *Journal of Retailing and Consumer Services*, 85, 104317. <https://doi.org/10.1016/j.jretconser.2025.104317>
13. Impact of big data analytics on sales performance in pharmaceutical organizations: The role of customer relationship management capabilities. *PLoS ONE*, 16(4), e0250229. <https://doi.org/10.1371/journal.pone.0250229>
14. Innovative data visualization for business intelligence: Enabling ad-hoc querying and predictive analysis. *International Journal for Multidisciplinary Research*, 6(5), 1-15. Retrieved from <https://www.ijfmr.com>
15. Personalized recommendation, behavior-based pricing, or both? Examining privacy concerns from a cost perspective. *Omega*, 133, 103223.
<https://doi.org/10.1016/j.omega.2024.103223>
16. The illusion of data-driven decision making – The mediating effect of digital orientation and controllers' added value in explaining organizational implications of advanced analytics. *Journal of Management Control*, 33, 403–446.
<https://doi.org/10.1007/s00187-022-00343-w>
17. Utilization of business intelligence tools among business intelligence users. *International Journal for Innovation Education and Research*, 9(6), 237-247.
Retrieved from <http://www.ijier.net>
18. Mondom, D. (2019). *Apostles for capitalism: Amway, movement conservatism, and the remaking of the American economy, 1959-2009* (Doctoral dissertation, Syracuse University). <https://surface.syr.edu/etd/1090>

19. DeCarlo, T. E., Dixon, A. L., Johnson, J., & Lam, S. K. (2025). Salespeople's experience with last-mile internal selling processes: Benefits and challenges. *Industrial Marketing Management*, 127, 1–13.
<https://doi.org/10.1016/j.indmarman.2025.03.004>
20. Mondom, D. (2018). Compassionate capitalism: Amway and the role of small-business conservatives in the New Right. *Modern American History*, 1(3), 343–361.
<https://doi.org/10.1017/mah.2018.37>
21. Liu, J., Chen, L., Luo, R., & Zhu, J. (2023). A combination model based on multi-angle feature extraction and sentiment analysis: Application to EVs sales forecasting. *Expert Systems with Applications*, 224, 119986.
<https://doi.org/10.1016/j.eswa.2023.119986>
22. Elalem, Y. K., Maier, S., & Seifert, R. W. (2023). A machine learning-based framework for forecasting sales of new products with short life cycles using deep neural networks. *International Journal of Forecasting*, 39(5), 1874–1894.
<https://doi.org/10.1016/j.ijforecast.2022.09.005>
23. Yan, X., Zhang, H., & Miao, Q. (2025). A novel sales forecast framework based on separate feature extraction and reconciliation under hierarchical constraint. *Computers & Industrial Engineering*, 201, 110875.
<https://doi.org/10.1016/j.cie.2025.110875>
24. Liu, J., Pan, H., Luo, R., Chen, H., Tao, Z., & Wu, Z. (2025). An electric vehicle sales hybrid forecasting method based on improved sentiment analysis model and secondary decomposition. *Engineering Applications of Artificial Intelligence*, 150, 110561. <https://doi.org/10.1016/j.engappai.2025.110561>
25. Wu, Z., Chen, X., & Gao, Z. (2023). Bayesian non-parametric method for decision support: Forecasting online product sales. *Decision Support Systems*, 174, 114019. <https://doi.org/10.1016/j.dss.2023.114019>
26. Mahin, M. P. R., Shahriar, M., Das, R. R., Roy, A., & Reza, A. W. (2025). Enhancing sustainable supply chain forecasting using machine learning for sales prediction. *Procedia Computer Science*, 252, 470–479.
<https://doi.org/10.1016/j.procs.2025.01.006>

27. Hu, H., Tan, D., Thaichon, P., Wang, B., & Zhu, Z. (2025). Grid-based market sales forecasting for retail businesses using automated machine learning and geospatial intelligence. *Expert Systems with Applications*, 284, 127869. <https://doi.org/10.1016/j.eswa.2025.127869>
28. Shao, J., Hong, J., Wang, M., & Wang, X. (2025). New energy vehicles sales forecasting using machine learning: The role of media sentiment. *Computers & Industrial Engineering*, 201, 110928. <https://doi.org/10.1016/j.cie.2025.110928>