Multi-Store System with Sales Forecasting in the Cooperative

Arnel C. Maghinay[1]
[1]Information Systems Department, College of Computer Studies,
Carlos Hilado Memorial State University, Negros Occidental, Philippines

John Gerald A. Pilar[2]
[2]General Education Department, College of Arts and Sciences,
Carlos Hilado Memorial State University, Negros Occidental, Philippines

Abstract

The study investigates the design and analysis of a multi-store sales forecasting system for cooperative retailers. The study uses a mixed-methods research approach that combines case study analysis with empirical research to model organizational processes and the technical antecedents of forecasting outcomes in a cooperative, multichannel setting. Using a case study research methodology, the study investigates actual operations. The study focuses on the social-technical aspects of employing advanced forecasting systems or the electronic connectivity of systems in geographically dispersed store networks. The quantitative component of the model is based on historical data, including past sales, inventory, and prices, as well as cooperative information system data on promotional activities. Statistical and regression models are employed to forecast sales, evaluate forecast accuracy, and identify the influence of antecedent variables on sales outcomes. They offer objective and data-driven insights that enhance decision-making. Design Science Research (DSR) gives relevance to the theoretical and practical dimensions of the development, deployment, and evaluation of a prototype forecasting system. Results show a very high level of user acceptance, with users reporting high perceived usefulness, usability, and ease of use. The system enhances productivity, simplifies routine activities, and enables informed decision-making in cooperative stores. In addition, the forecasting system is incorporated into a holistic multi-store e-commerce system that facilitates effective data management, flexible transaction processing, and multiple income streams. Overall, the study verifies that highly advanced forecasting systems have the possible to significantly improve efficiency, inventory management, and coordination in cooperative retail networks.

Keywords: multi-store cooperative systems; sales forecasting; regression analysis; machine learning; Post-Study System Usability Questionnaire; operational efficiency; inventory management

1. Introduction

A multi-store system is a popular form of retail firms that tend to be made up of many large stores, which are part of a national chain, and they offer a wide variety (Haltiwanger et al., 2009). For such applications, and in particular for cooperative models, forecasting sales well is essential to the operation and optimization of a system (Ahaggach et al., 2024; Mitra et al., 2023). In a report on the history of cooperatives, ‘Defining cooperative’ was defined by the International Cooperative Alliance as an autonomous association of persons who unite voluntarily to meet their common economic, social and cultural needs and aspirations through a business which they own collectively and operate democratically (Benavides & Ehrenhard, 2021). This architecture often calls for a delicate hold between centralised control and regional autonomy making sales planning both easier and harder (Mitronen & Möller, 2003).

It is through sales forecasting that one may efficiently administer various dimensions of business including-production, strategic planning, supply chain management, market, warehousing- logistics and resource allocation etc. (Chintapanti & Maiti, 2023). Providers such as Amazon and Walmart have to estimate the sales demand more precisely in order to maintain the product inventory at a minimum level (Hewamalage et al., 2021). Even manufacturing companies engaged in the food and drink business find sales forecasting extremely important, as they face issues such as limited space, limited manpower, and an increasing number of people making purchases online (Mitra et al., 2023). Many Lynn University students work in retail and at the stores of our local mall's tenants, effective sales planning is key so they don't throw good perishables away, which can be costly not only to their bottom line but also bad for our planet (Fries & Ludwig, 2022). To maintain the level of services, not to lose clients at peak times, and not to refuse clients themselves or interrupt their orders (Groene & Zakharov, 2024).

Sales Forecasting is necessary but difficult in multi-store and federation scenarios. This can include sociotechnical challenges in deploying machine learning-based forecasts (Fries & Ludwig, 2022), handling demand variability when launching promotion events and the inherent challenge of new product forecasting due to lack of historical data records (Eksoz et al., 2014). Additionally, forecasting borders among organizations can have issues that may drive operational and financial planning to not be aligned (Lichen, 2013). The complexity increases due to the sales consolidation across different levels, from single products to complete chains of stores, that influence both strategic and operational decisions (Fildes et al., 2019). Because of these complexities, this study aims at exploring the approaches, theories and focused outcomes of sales forecasting in multi-store cooperative systems.

2. Related Works

The successful forecasting of sales is a fundamental prerequisite for efficient routine operations and strategic planning in retail, in particular if it concerns multi-store systems and cooperative organisations. In a variety of retail contexts the accurate forecasting is crucial for inventory management, cost reduction and customer satisfaction (Fildes et al., 2019; Gai, 2025; Mentzer et al., 1999). The difficulties of obtaining accurate sales predictions in multi-store systems are well-documented, including seasonality, promotion effects, and the difficulty of combining sales numbers across different levels (Ali & Pinar, 2016; Fildes et al., 2019; Theodorou et al., 2021).

2.1 Advanced Forecasting Techniques

The development of sales forecasting has evolved from classical statistics to advanced techniques, especially machine learning and deep learning algorithms. These advanced methods are becoming more prevalent in order to cope with the complexity of short-term retail sales data, which are usually very volatile and have a large number of factors affecting them (Eglite & Birzniece, 2022; Gai, 2025; Sun, 2024). For example, as it was demonstrated in earlier works (Lim, 2014), deep learning algorithms can dramatically increase the accuracy of prediction and help retailers to manage inventory and operational costs in a more efficient manner. Previous studies on the effectiveness of many ML/DL models in retail sales prediction have focused on their capacity to deal with complex data patterns and facilitate better decision-making (Mitra et al., 2022; Suresh & Suresh, 2023). The implementation of these approaches in various retail channels, which include both supermarket chains and food factories, highlights their good adaptability to different operational environments (Kao & Chueh, 2022).

2.2 Usability of Forecasting Systems

The realization and deployment of forecasting systems have a huge impact on their effectiveness, not only due to the technical accuracy but also the usability and user acceptance of these systems. The Post-Study System Usability Questionnaire has been acknowledged as a tool for measuring satisfaction and usability of use in different environments (Rosa et al., 2015). Apart from organizational protocols, information sharing among stakeholders and the availability of product knowledge also play a crucial role in the effective adoption and use of forecasting support systems (Asimakopoulos & Dix, 2013). The usability of web applications and information systems has been the main focus of studies that have employed PSSUQ and have shown that user satisfaction will be a result of higher-level usage (Lestari & Bahri, 2020). The evaluation of usability indicators, such as the PSSUQ measurement, enables decision-making by providing user information about the systems that are tailored to their needs (Macías & Borges, 2023).

2.3 Challenges in Implementation

There are difficulties involved in implementing advanced sales forecasting solutions in multi-store and cooperative settings. One major difficulty is the integration of socio-technical aspects, where technological solutions must be very delicately embedded into the existing work practices and the organizational processes (Fries & Ludwig, 2022). Demand fluctuations during sales periods, the lack of historical data for new product lines, and the complications of data consolidation among the different levels of the organization are some of the factors that make accurate forecasting difficult (Fildes et al., 2019; Fries & Ludwig, 2022). The cooperatives need to have strong data infrastructure and make a huge investment in technology and training which are very crucial for them to be able to apply sophisticated forecasting methods effectively.

2.4 Collaborative Forecasting

The use of collaborative forecasting techniques is frequently suggested as a way to improve the supply chain performance and efficiency, particularly in multi-echelon systems. Such partnerships entail the exchange of both information and expertise among the different partners involved in the supply chain, thus resulting in a more precise and collective forecast (Eksoz et al., 2014). The influence of collaborative forecasting on forecast accuracy is not straightforward, as it is usually regarded as a positive factor; some research indicates that it can actually be a double-edged sword and may not always yield better accuracy depending on the situation, such as the organization's decision regarding the allocation of resources between forecasting and order quantities (Galbreth et al., 2015). However, if the process is well-managed, collaborative forecasting can lead to better supply-chain coordination, which in turn would support short-term planning activities such as production scheduling and inventory management (Belle et al., 2020; Kurtuluş et al., 2011). Still, full implementation of this forecast method comes with difficulties, which means that there should be a very careful assessment of its feasibility and value at every point along the supply chain (Småros, 2006).

3. Materials And Methods

The research design in the study incorporates the use of various methodologies that will allow a complete analysis of sales forecasting in multi-store cooperative systems. The methodology is capable of integrating both qualitative depth and quantitative rigor, which has guaranteed a sound analysis (Barrientos & Pilar, 2026) of the technical and organizational factors.

3.1 Design

Case Study Method

A case study approach will be key to the comprehension of the complex processes in a single or a series of multi-store cooperatives. It is a way to take an in-depth look at the real-world operational issues and to be able to forecast mechanisms that currently exist in complex organizational structures (Abolghasemi et al., 2020). According to Riis (2012), case study research is applicable when theory is infantile, the researcher has minimal control, and the focus is on a current phenomenon in a real-life setting. Riis notes this makes the methodology particularly appropriate for information systems research, given the strong relationship between information systems and their organizational contexts. Such practice would help identify the socio-technical issues entailing the implementation of new technologies such as machine learning to predict sales (Fries & Ludwig, 2022; Groene & Zakharov, 2024). The case studies can be useful in comprehending the factors that lead to the implementation of AI-based solutions in companies (Groene & Zakharov, 2024).

3.2 Empirical Analysis

The important part of this work includes the quantitative empirical analysis, which involves studying the past sales data, inventory, promotion actions, and other relevant data of the chosen cooperatives. This involves collecting and analyzing numerical data with the aim of identifying the patterns, correlation and cause relationships. Sales forecasting is applied with the assistance of regression models to predict the upcoming sales based on sales events in the past and may be utilized to generate future revenue and control the sales adequately (Xu, 2023; Zhang, 2023). Sales forecasting empirical research is often based on the use of statistical modeling and machine learning algorithms to process large amounts of data and forecast future sales, as in a variety of retail settings (Ali & Pinar, 2016; Fildes et al., 2019). As one example, the large retail chain sales data tend to have such characteristics as high volatility, skewness, etc., because of the effect of price changes, promotions, and seasonal effects, and such precise levels of sales forecasting of items is a complicated task (Ma & Fildes, 2020). It is a quantitative aspect that introduces objective evidence to justify findings and enables the evaluation of the model accuracy and influences of different factors on sales performance (Ali & Gürlek, 2020).

3.3 System Design and Evaluation

The paper applies a system design and evaluation methodology, which is the Design Science Research (DSR) approach to the development and a transition process to a prototype system. The Design Science Research (DSR) field is recognized as a key area in the disciplines aiming at the creation of successful artifacts and ultimately wants to amplify human and organizational potential by means of the introduction of new and inventive artifacts (Hevner et al., 2004; Peffers et al., 2007). This Design Science Research (DSR) is an issue analysis and resolution process that results in the creation of artifacts that need different methods of evaluation based on the type of artifact (Müller et al., 2024). The approach of Design Science Research (DSR) includes the essentials of principles, practices and procedures for conducting such research, which provides a conceptual model of conducting and evaluating DSR (Peffers et al., 2007). This strategy will guarantee that the forecasting system developed is not only satisfactory in theory but also practically usable and effective in the context of the collaboration.

3.4 Procedures

Review of Literature

An adequate literature review is necessary to put the study into context of the existing academic literature regarding multi-tiered systems, sales forecasting, and collaborative supply chain management. This includes the synthesis of existing information, a gap in the research, and finding a theoretical basis on the study (Ahaggach et al., 2024). The review considers various analytics models, including the old-fashioned statistical techniques such as regression analysis up to the complex machine learning and deep learning algorithms and conditions that affect the usability of forecasting systems (Magrini, 2024).

3.5 Data Collection

Quantitative Data Collection

The purpose of collecting quantitative data for this analysis was to extract historical sales, inventories, prices and promotions data from the cooperative databases related to the present. For the purpose of training and authenticating forecasting models, and also for conducting an authentic empirical analysis, this information is invaluable. It is the difficulty of using big data analytical tools to extract meaningful information from customer retail transactions data captured from point of sale systems and RFID systems, which in turn helps improve the business processes and optimize the inventory (Kholod et al., 2024). Inventory management is done using accurate information to minimize mistakes and the associated time wastage (Tong, 2025).

Instruments

Data extraction tools: As a data extraction tool is understood to be any application that can assist in recovering data from a cooperative's POS and inventory system, such tools are referred to as web data extraction systems. Web data extraction systems encompass a broad swathe of computer applications that extract data from multiple web-based repositories for subsequent processing and storage for future use (Ferrara et al., 2014). Organizations use automated systems to process data, so as to assure that financial and other records are properly maintained (Saout et al., 2024). Data extraction is also used to pinpoint and recover information from documents which other tools (Pilar, 2024) of a custom design are programmed to retrieve (Afifi et al., 2023).

Statistical Package: Tools like Excel and SPSS were employed for the computation, construction, and analysis of the data. Excel is often criticized as not being a statistical program, but is recognized as a spreadsheet program and is used for statistical analysis because it is relatively easy to learn and is ubiquitous (Dembe et al., 2011; Paura & Arhipova, 2012; Todorova, 2019). Other fully fledged professional commercial statistical systems like SPSS and SAS have been shown to have more sophisticated forms of analysis (Dembe et al., 2011; Paura & Arhipova, 2012). SPSS is very powerful for business and marketing data analysis: it supports the forecasting of sales quantity based on unit price, advertising expenditures, and an assortment of regression and ANOVA algorithms (Thu & Cho, 2019).

Interview Protocols: Longitudinal studies require standard protocols to maintain uniformity in questioning and the collection of data (Pilar, 2025) from all the stakeholders involved. In this case, an interview protocol serves as an important instrument to provide quality qualitative data, relative accuracy, and relevance (Shoozan & Mohamad, 2024). Moreover, interview guides consist of questions that are aligned with and derived from the objectives of the study, prepared thematically to capture varied cross-sectional perceptions (Alméstar et al., 2022). With the help of protocols, semi-structured interviews blend the constants with the variability in the reactions to the questions (Hunter, 2012; Kallio et al., 2016).

Like other Microsoft Office products, Microsoft Project specializes in both project planning and management. In this study, the Gantt chart was a part of a powerful project-planning tool that creates a pictorial diagram of a project schedule, thus providing a review of timelines like start and end dates, alongside assisting in progress monitoring (Abdelazim, 2024; Murlimanju & Prabhu, 2023). It is said that, the Gantt charts are ubiquitous in the field of project management in coordination of tasks and parallel activities of multi-faceted undertakings, and in scholarly activities for the planning of tasks (Murlimanju & Prabhu, 2023; Obasuyi, 2025).

3.6 Participants/Subjects

The research captures the essence of the cooperative, gaining a thorough grasp of the participants and their respective sales forecasting activities.

Cooperative Executive: Such persons deliver tactical forecasting system insights and since decision-making at the apex levels of the forecasting system, they dictate the goals and restraints of the system. Their willingness, along with a comprehension of new technologies, drives the digital transformation and AI-based solutions, as adopted by their companies (Groene & Zakharov, 2024).

Store Managers: Sales managers analyze daily operations alongside customer interactions, enabling them to provide practical advice greater than any theory on the drivers of sales, along with local market conditions. Sales managers savage the ebb and flow of sales and of sales, especially when promotional activities are involved (Abolghasemi et al., 2020).

IT Staff: These technical wizards understand the cooperative's foundational data environment and intellectual framework from the perspective of data utilization and the interconnections of its components to extraction, and therefore, their knowledge is indispensable (Bandara et al., 2023). Without them, huge amounts of data would remain untamed, unable to be integrated with the Enterprise Resource Planning (ERP) systems and big data technologies, with other engineering forged chains.

Data Scientists/Analysts: These specialists, alongside others, provide and maintain engineering resources and configuration of controls to drive the network of centres so that the models of forethinking are chosen and engineered. These specialists carry out expositions on the varieties Sales and Forecasting systems to improve operational philosophies, branding, and business revenue along with AI that helps with the Sales and Customer Relationship Management database systems (Habel et al., 2023).

4. Results And Discussion

4.1 Perceived Usefulness

In Table 1 on the "Perceived Usefulness", the results suggest the respondents are in agreement about the system's usefulness, given the average mean score of 1.29 in perceived usefulness, which equates to 'Strongly Agree.' This indicates that both system users and employees believe that the system is an effective solution to increasing productivity in their respective roles. This supports existing theories that explain the construct of perceived usefulness as an important factor in the acceptance and success of any new technology. It further indicates that the perception of a system improving work outcomes is a predominant factor in system acceptance, which continues to be a gap in theory that links system quality and information quality to performance outcomes (Davis, 1989, 1993; Saputra et al., 2023; Yang & Yoo, 2003).

4.2 Perceived Ease of Use

The system achieved a high average score of 1.34 for "Perceived Ease of Use" (PEOU), indicating that users "Strongly Agree" that the platform is straightforward and free from complexity. This result aligns with foundational academic definitions of PEOU as the degree to which a user believes a system is effort-free, a perception that is vital for initial technology acceptance and long-term adoption (Davis, 1989; Jo & Park, 2023). In this manner, by emphasizing simplicity and ease of comprehension, the system effectively minimizes the cognitive workload, thereby reducing the mental effort required for operation and directly enhancing user satisfaction (Bashir et al., 2022; Stadler et al., 2024). Furthermore, this preference for cognitive ease significantly influences user behavior, as technologies that simplify tasks are more likely to be used sustainably and with positive intent (Dendrinos & Spais, 2023; Liu, 2024). Therefore, the manifestly strong agreement result of the PEOU score confirms that the system successfully meets user expectations for a seamless, accessible interface that prioritizes operational efficiency.

4.3 Perceived Usability

The perceived usability of the system, as shown in Table 1, receives an average score of 1.28, representing Strongly Agree. The perceived usability of a system, encompassing its effectiveness, efficiency, and user satisfaction, is a critical metric consistently supported by academic research. Ferreira et al. (2019) define usability as a software quality characteristic that includes efficiency, effectiveness, and user satisfaction. This aligns with the International Standards Organization's requirements for usability, which describe the extent to which users can achieve goals with effectiveness, efficiency, and satisfaction. Further, Syahrozad and Subriadi (2024) categorize usability from a user's perspective as an evaluation of system efficiency and effectiveness, explicitly including user satisfaction as a key aspect. Similarly, the Usefulness, Satisfaction, and Ease of Use Questionnaire, investigated by Gao et al. (2018), directly measures subjective usability through dimensions such as usefulness, ease of use, ease of learning, and satisfaction. The impact of these factors is further evidenced by Lewis and Sauro (2023), who found that perceived ease of use and perceived usefulness significantly account for variations in overall user experience, likelihood to recommend, and intention to use. These collective insights highlight that a system scoring high in perceived usability is indeed seen by users as effective in achieving their goals, efficient in its operation, and satisfactory to interact with (Alzahrani & Alnanih, 2020).

Table 1 Mean Results of Perceived Usefulness, Ease of Use, and Usability

	N	Mean	Std. Deviation	Interpretation
Perceived Usefulness	30	1.29	0.13	Strongly Agree

Perceived Ease of Use	30	1.34	0.13	Strongly Agree
Perceived Usability	30	1.28	0.29	Strongly Agree

Looking into this Multi-Store System Conceptual Framework Business Model as shown in Figure 1, which demonstrates that the e-commerce system depicted represents a comprehensive multi-store digital marketplace that integrates multiple transaction models, product types, competitive mechanisms, and revenue streams into a unified platform architecture (Karuppuchamy, 2025; Poniatowski et al., 2021; Staub et al., 2021). Such platforms centralize data flows and normalize marketplace-specific requirements, automating processes to provide consistent customer experiences across various channels (Karuppuchamy, 2025). These platforms are often conceptualized as nested hierarchies of systems interacting with their environment, with a modular technological architecture comprising core components, interfaces, and complements (Poniatowski et al., 2021; Staub et al., 2021).

It supports all principal forms of electronic exchange, including business-to-consumer (B2C), business-to-business (B2B), consumer-to-consumer (C2C), and consumer-to-business (C2B) interactions, thereby enabling firms, individuals, and intermediaries to engage in diverse market relationships within a single ecosystem (Buron, 2018; Воробьева et al., 2021; Cano et al., 2023). Digital marketplaces facilitate transactions and business activities as online marketplaces where sellers offer products or services to consumers, and act as impartial intermediaries connecting two parties (Cano et al., 2023). B2C involves businesses selling to individuals, B2B involves businesses transacting with other businesses, C2C facilitates transactions between individuals, and C2B allows consumers to offer products or services to businesses (Buron, 2018; Воробьева et al., 2021; Raju & Feldman, 2017).

The platform's value proposition extends beyond the sale of physical goods and services to encompass data-driven offerings such as packaged marketing information, digital advertising space, and agency-based services, positioning the system as an active market intermediary rather than a passive storefront (Hänninen & Smedlund, 2021; Muthers & Wismer, 2022). Online marketplaces reduce transaction costs, facilitating economic interactions and enabling easier entry for sellers, thereby acting as active intermediaries between customers and service providers (Hänninen & Smedlund, 2021; Luca, 2017). Platforms can adopt either a 'merchant' mode, by buying and reselling products, or a 'two-sided platform' mode, by enabling affiliated sellers to sell directly to buyers, indicating an active intermediary role (Hagiu, 2007). Data generated by quantified products can be exploited using data-driven services on data marketplaces, which are often considered infrastructure for trading data and related services (Sandkuhl, 2023).

Competitive advantage is achieved through the coexistence of multiple pricing and matching mechanisms, including fixed pricing, real-time buyer–seller matching, reverse pricing models, and formalized tendering processes, which collectively enhance market efficiency, liquidity, and flexibility across varying transaction contexts (Bichler et al., 2002; Lim & Lee, 2003). Flexible pricing, encompassing differential pricing and dynamic mechanisms like auctions, is increasingly used in business-to-business e-commerce (Bichler et al., 2002). The design of B2B e-marketplaces often considers various architectures for buyer-carts, along with feasible combinations of marketplace operators and pricing mechanisms (Lim & Lee, 2003).

Revenue generation is correspondingly diversified, combining transaction-based commissions, advertising income, and the monetization of aggregated user and market data, thereby reducing dependency on any single income source and reinforcing platform sustainability (Bayashot, 2025; Lefouili & Madio, 2021; Park et al., 2020; Pfeiffer, 2019). Platforms often generate revenue by charging fees for transactions and advertising activities (Lefouili & Madio, 2021; Park et al., 2020). Monetization models for SuperApps, for instance, categorize revenue strategies into commission-based revenue, subscription services, and advertising, often relying on hybrid mechanisms that combine commissions with data-driven advertising (Bayashot, 2025). The remuneration of platforms can also come from prices charged on both sides of the market, such as transaction fees (Pfeiffer, 2019).

4.4 E-Commerce System Analysis

Modern e-commerce functions as a complex ecosystem integrated by diverse transactional frameworks ranging from multi-store B2C and high-value B2B models to peer-driven C2C and C2B structures that facilitate the global exchange of physical and digital assets (Abdalla et al., 2024; Ahi et al., 2022; Cano et al., 2023; Gu et al., 2023; Hänninen et al., 2019). This infrastructure is supported by critical brokerage, agency, and logistics services that streamline commercial interfacing (Bakos, 1998; Barnes & Hinton, 2007). To maintain market efficiency, platforms have evolved beyond fixed pricing to utilize real-time matching algorithms, reverse auctions, and formal procurement tenders (Aouad & Sabán, 2022; Herrmann & Cobo, 2024; Spann et al., 2017). These operations are sustained by multifaceted revenue streams, including sales commissions and digital advertising, as well as the increasingly dominant practice of data monetization, where aggregated user insights are leveraged for third-party analysis under the paradigm of surveillance capitalism (Choi & Mela, 2019; Gradwohl & Tennenholtz, 2023; Hu & Zhang, 2022; Zuboff, 2015).

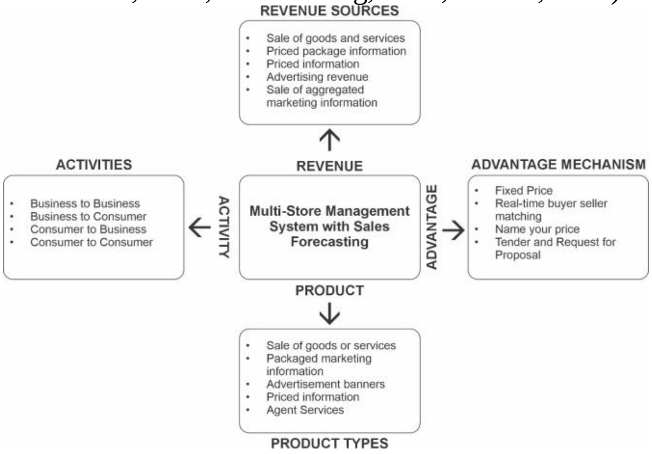

Figure 1. Multi-Store System Conceptual Framework Business Model

Looking into the whole picture, the system exemplifies a mature, data-intensive e-commerce model that leverages technological intermediation, multi-sided participation, and diversified monetization to function as a scalable and resilient digital marketplace. Hence, it is timely and feasible for cooperatives that need these features, including multi-store sales forecasting, to adopt them.

5. Conclusion

It is indeed the application of sophisticated sales forecasting techniques to multi-store cooperative systems that offers a number of advantages, such as increased operational efficiency and support for achieving strategic goals. Accurate direct sales information is useful for enhancing stock control, lowering costs and increasing customer satisfaction in the broad array of retail environments where cooperatives operate.

Practical adoption of forecasting in cooperatives requires navigating socio-technical complexities, such as managing promotional volatility and the data scarcity associated with new product launches. Success depends on harmonizing centralized strategies with local branch autonomy through standardized data collection and deep organizational integration across all locations. Finally, model performance must be measured using tailored business metrics rather than generic statistical indicators to ensure the results align with specific commercial objectives and operations.

The implementation of modern sales forecasting is a major strategy goal for multi-outlet cooperative enterprises. Through a commitment to thorough data collection, advanced analytical models and thoughtful implementation and ongoing evaluation, cooperatives can dramatically enhance how they respond to the market, utilize resources more effectively and solidify their leadership role in the evolving retail environment. This comprehensive methodology ensures that each new tech can drive actual value in the entire cooperative ecosystem. Henceforward, this system on multi-store with sales forecasting in the cooperatives would be valuable and usable among cooperatives.

Acknowledgments

The authors appreciate Carlos Hilado Memorial State University (CHMSU), headed by Dr. N.P. Mangulabnan, as the university president, for approving its funding for publication and for its steadfast support for the conception and completion of this research project to benefit teachers and new-era learners. The Research and Development Services (RDS) of CHMSU encourages the completion of the project through its implementation and provides technical support. On the other hand, the ethical protocol of this study was observed and followed in accordance with the standards. Any residual errors in the manuscript are their full responsibility of the authors.

Declaration of generative AI and AI-assisted technologies in the writing process.

ChatGPT-4 and Grammarly are utilized to improve the manuscript's grammar and sentence structures.

REFERENCES

1. Abdalla, S., Amankwah-Amoah, J., Hirekhan, M., & Temerak, M. S. (2024). Unlocking the potentials of hybrid business models in the sharing economy: An integrative review and new research agenda. Information Technology for Development, 1. https://doi.org/10.1080/02681102.2024.2368536

2. Abdelazim, Z. (2024). Project Management—Gantt Chart. SSRN Electronic Journal. https://doi.org/10.2139/ssrn.4453514

3. Abolghasemi, M., Hurley, J., Eshragh, A., & Fahimnia, B. (2020). Demand forecasting in the presence of systematic events: Cases in capturing sales promotions. International Journal of Production Economics, 230, 107892–107892. https://doi.org/10.1016/j.ijpe.2020.107892

4. Afifi, M., Stryhn, H., & Sánchez, J. (2023, December). Data extraction and comparison for complex systematic reviews: A step-by-step guideline and an implementation example using open-source software. In Systematic Reviews (Vol. 12, Issue 1). BioMed Central. https://doi.org/10.1186/s13643-023-02322-1

5. Ahaggach, H., Abrouk, L., & Lebon, É. (2024). Systematic Mapping Study of Sales Forecasting: Methods, Trends, and Future Directions. Forecasting, 6(3), 502. https://doi.org/10.3390/forecast6030028

6. Ahi, A., Sinkovics, N., & Sinkovics, R. R. (2022). E-commerce Policy and the Global Economy: A Path to More Inclusive Development? Management International Review, 63(1), 27. https://doi.org/10.1007/s11575-022-00490-1

7. Ali, Ö. G., & Gürlek, R. (2020). Automatic Interpretable Retail forecasting with promotional scenarios. International Journal of Forecasting, 36(4), 1389–1406. https://doi.org/10.1016/j.ijforecast.2020.02.003

8. Ali, Ö. G., & Pinar, E. (2016). Multi-period-ahead forecasting with residual extrapolation and information sharing—Utilizing a multitude of retail series. International Journal of Forecasting, 32(2), 502–517. https://doi.org/10.1016/j.ijforecast.2015.03.011

9. Alméstar, M., Sastre-Merino, S., Velón, P., Martínez, M., Marchamalo, M., & Calderón-Guerrero, C. (2022). Schools as levers of change in urban transformation: Practical strategies to promote the sustainability of climate action educational programs. Sustainable Cities and Society, 87, 104239–104239. https://doi.org/10.1016/j.scs.2022.104239

10. Alzahrani, H., & Alnanih, R. (2020). A Design Study to Improve user Experience of a Procedure Booking Software in Healthcare. International Journal of Advanced Computer Science and Applications, 11(11). https://doi.org/10.14569/ijacsa.2020.0111132

11. Aouad, A., & Sabán, D. (2022). Online Assortment Optimization for Two-Sided Matching Platforms. Management Science, 69(4). https://doi.org/10.1287/mnsc.2022.4464

12. Asimakopoulos, S., & Dix, A. (2013). Forecasting support systems technologies-in-practice: A model of adoption and use for product forecasting. International Journal of Forecasting, 29(2), 322–336. https://doi.org/10.1016/j.ijforecast.2012.11.004

13. Bakos, Y. (1998). The emerging role of electronic marketplaces on the Internet. Communications of the ACM, 41(8), 35–42. https://doi.org/10.1145/280324.280330

14. Bandara, F., Jayawickrama, U., Nuwangi, S. M., Olan, F., Alamoudi, H., & Alharthi, M. (2023). Enhancing ERP Responsiveness Through Big Data Technologies: An Empirical Investigation. Information Systems Frontiers, 26(1), 251–275. https://doi.org/10.1007/s10796-023-10374-w

15. Barnes, D., & Hinton, M. (2007). Developing a framework to analyse the roles and relationships of online intermediaries. International Journal of Information Management, 27(2), 63. https://doi.org/10.1016/j.ijinfomgt.2006.04.003

16. Barrientos, R. L. C., & Pilar, J. G. A. (2026). After mining catastrophe: The language of economic survival of the Sipalay mine people at Sipalay, Negros Occidental, Philippines. Journal of Degraded and Mining Lands Management, 13(1), 9239–9257. https://doi.org/10.15243/jdmlm.2026.131.9239

17. Bashir, T., Tan, Z., Sadiq, B., Niaz, U., Anjum, F., & Mahmood, H. (2022). An assessment of influential factors developing the intention to use social media sites: A technology acceptance model based approach. Frontiers in Psychology, 13. https://doi.org/10.3389/fpsyg.2022.983930

18. Bayashot, Z. A. (2025). Monetization Models of SuperApps. Journal of Software Engineering and Applications, 18(7), 249–267. https://doi.org/10.4236/jsea.2025.187015

19. Belle, J. V., Guns, T., & Verbeke, W. (2020). Using shared sell-through data to forecast wholesaler demand in multi-echelon supply chains. European Journal of Operational Research, 288(2), 466. https://doi.org/10.1016/j.ejor.2020.05.059

20. Benavides, A. F. C., & Ehrenhard, M. (2021). Rediscovering the Cooperative Enterprise: A Systematic Review of Current Topics and Avenues for Future Research [Review of Rediscovering the Cooperative Enterprise: A Systematic Review of Current Topics and Avenues for Future Research. VOLUNTAS International Journal of Voluntary

and Nonprofit Organizations, 32(5), 964. https://doi.org/10.1007/s11266-021-00328-8

21. Bichler, M., Kalagnanam, J., Katırcıoğlu, K., King, A. J., Lawrence, R. D., Lee, H. S., Lin, G.-D., & Lu, Y. (2002). Applications of flexible pricing in business-to-business electronic commerce. IBM Systems Journal, 41(2), 287–302. https://doi.org/10.1147/sj.412.0287

22. Buron, C. (2018). A multiagent system for an invoice marketplace. HAL (Le Centre Pour La Communication Scientifique Directe).

23. Воробьева, Е. С., Yusubova, Z. A., & Гасанов, М. А. (2021). Development of Marketplaces in the Context of Digital Transformation as a Result of Structural Shifts in the Economy. Vestnik Universiteta, (2), 95–100. https://doi.org/10.26425/1816-4277-2021-2-95-100

24. Cano, J. A., Pineda, A. A. L., Campo, E. A., & Henao, S. A. F. (2023). Sustainable business models of e-marketplaces: An analysis from the consumer perspective. Journal of Open Innovation Technology Market and Complexity, 9(3), 100121. https://doi.org/10.1016/j.joitmc.2023.100121

25. Chintapanti, A., & Maiti, S. (2023). Efficient approach for Predicting Sales using Supervised Machine Learning Algorithms. https://doi.org/10.21203/rs.3.rs-3255369/v1

26. Choi, H., & Mela, C. F. (2019). Monetizing Online Marketplaces. Marketing Science. https://doi.org/10.1287/mksc.2019.1197

27. Davis, F. D. (1989). Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology. MIS Quarterly, 13, 319–340. https://doi.org/10.2307/249008

28. Davis, F. D. (1993). User acceptance of information technology: System characteristics, user perceptions and behavioral impacts. International Journal of Man-Machine Studies, 38(3), 475. https://doi.org/10.1006/imms.1993.1022

29. Dembe, A. E., Partridge, J., & Geist, L. (2011). Statistical software applications used in health services research: Analysis of published studies in the U.S. BMC Health Services Research, 11(1). https://doi.org/10.1186/1472-6963-11-252

30. Dendrinos, K., & Spais, G. S. (2023). An investigation of selected UTAUT constructs and consumption values of Gen Z and Gen X for mobile banking services and behavioral intentions to facilitate the adoption of mobile apps. Journal of Marketing Analytics, 12(3), 492. https://doi.org/10.1057/s41270-023-00271-1

31. Eglite, L., & Birzniece, I. (2022). Retail Sales Forecasting Using Deep Learning: Systematic Literature Review. Complex Systems Informatics and Modeling Quarterly, (30), 53–62. https://doi.org/10.7250/csimq.2022-30.03

32. Eksoz, C., Mansouri, S. A., & Bourlakis, M. (2014). Collaborative forecasting in the food supply chain: A conceptual framework. International Journal of Production Economics, 158, 120. https://doi.org/10.1016/j.ijpe.2014.07.031

33. Ferrara, E., Meo, P. D., Fiumara, G., & Baumgartner, R. (2014). Web data extraction, applications and techniques: A survey. Knowledge-Based Systems, 70, 301–323. https://doi.org/10.1016/j.knosys.2014.07.007

34. Ferreira, J. M., Acuña, S. T., Dieste, Ó., Vegas, S., Santos, A., Rodríguez, F. D., & Juristo, N. (2019). Impact of usability mechanisms: An experiment on efficiency, effectiveness and user satisfaction. Information and Software Technology, 117, 106195. https://doi.org/10.1016/j.infsof.2019.106195

35. Fildes, R., Ma, S., & Kolassa, S. (2019). Retail forecasting: Research and practice. International Journal of Forecasting, 38(4), 1283. https://doi.org/10.1016/j.ijforecast.2019.06.004

36. Fries, M., & Ludwig, T. (2022). Why are the Sales Forecasts so low?' Socio-Technical Challenges of Using Machine Learning for Forecasting Sales in a Bakery. Computer Supported Cooperative Work (CSCW, 33(2), 253. https://doi.org/10.1007/s10606-022-09458-z

37. Gai, T. (2025). Machine Learning Approaches for Accurate Sales Forecasting in Supermarket Chains. In Learning and analytics in intelligent systems (p. 279). Springer International Publishing. https://doi.org/10.1007/978-3-031-85952-6_26

38. Galbreth, M. R., Kurtuluş, M., & Shor, M. (2015). How collaborative forecasting can reduce forecast accuracy. Operations Research Letters, 43(4), 349–353. https://doi.org/10.1016/j.orl.2015.04.006

39. Gao, M., Kortum, P., & Oswald, F. L. (2018). Psychometric Evaluation of the USE (Usefulness, Satisfaction, and Ease of use) Questionnaire for Reliability and Validity. Proceedings of the Human Factors and Ergonomics Society Annual Meeting, 62(1), 1414. https://doi.org/10.1177/1541931218621322

40. Gradwohl, R., & Tennenholtz, M. (2023). Selling Data to a Competitor. SSRN Electronic Journal. https://doi.org/10.2139/ssrn.4343686

41. Groene, N., & Zakharov, S. (2024). Introduction of AI-based sales forecasting: How to drive digital transformation in food and beverage outlets. Discover Artificial Intelligence, 4(1). https://doi.org/10.1007/s44163-023-00097-x

42. Gu, W., Luo, J., Yu, X., Zhang, W., & Li, B. (2023). Dynamic decisions between sellers and consumers in online second-hand trading platforms: Evidence from C2C transactions. Transportation Research Part E Logistics and Transportation Review, 177, 103257. https://doi.org/10.1016/j.tre.2023.103257

43. Habel, J., Alavi, S., & Heinitz, N. (2023). A theory of predictive sales analytics adoption. AMS Review. https://doi.org/10.1007/s13162-022-00252-0

44. Hagiu, A. (2007). Merchant or Two-Sided Platform? Review of Network Economics, 6(2). https://doi.org/10.2202/1446-9022.1113

45. Hänninen, M., Mitronen, L., & Kwan, S. K. (2019). Multi-sided marketplaces and the transformation of retail: A service systems perspective. Journal of Retailing and Consumer Services, 49, 380. https://doi.org/10.1016/j.jretconser.2019.04.015

46. Hänninen, M., & Smedlund, A. (2021). Same Old Song with a Different Melody: The Paradox of Market Reach and Financial Performance on Digital Platforms. Journal of Management Studies, 58(7), 1832–1868. https://doi.org/10.1111/joms.12701

47. Herrmann, H., & Cobo, M. J. (2024). Bidding for B2B or B2G tenders: Toward the adoption of pricing models in practice. Management Review Quarterly, 75(2). https://doi.org/10.1007/s11301-024-00424-1

48. Hevner, March, M., Park, J., & Ram, R. (2004). Design Science in Information Systems Research. MIS Quarterly, 28(1), 75–75. https://doi.org/10.2307/25148625

49. Hewamalage, H., Bergmeir, C., & Bandara, K. (2021). Global models for time series forecasting: A Simulation study. Pattern Recognition, 124, 108441. https://doi.org/10.1016/j.patcog.2021.108441

50. Hu, H., & Zhang, H. (2022). Commissions and Profits on e-Tailing Platforms. SSRN Electronic Journal. https://doi.org/10.2139/ssrn.3905726

51. Hunter, M. G. (2012). Creating Qualitative Interview Protocols. International Journal of Sociotechnology and Knowledge Development, 4(3), 1–16. https://doi.org/10.4018/jskd.2012070101

52. Jo, H., & Park, D.-H. (2023). Mechanisms for successful management of enterprise resource planning from user information processing and system quality perspective. Scientific Reports, 13(1). https://doi.org/10.1038/s41598-023-39787-y

53. Kallio, H., Pietilä, A.-M., Johnson, M., & Kangasniemi, M. (2016, May). Systematic methodological review: Developing a framework for a qualitative semi-structured interview guide. In Journal of Advanced Nursing (Vol. 72, Issue 12, pp. 2954–2965). Wiley. https://doi.org/10.1111/jan.13031

54. Kao, C.-Y., & Chueh, H.-E. (2022). Deep Learning Based Purchase Forecasting for Food Producer-Retailer Team Merchandising. Scientific Programming, 2022, 1–9. https://doi.org/10.1155/2022/2857850

55. Karuppuchamy, S. (2025). Unified marketplace optimization: Building a scalable tech stack for multi-channel eCommerce. World Journal of Advanced Engineering Technology and Sciences, 15(3), 1039–1050. https://doi.org/10.30574/wjaets.2025.15.3.1012

56. Kholod, M., Celani, A., & Ciaramella, G. (2024). The Analysis of Customers' Transactions Based on POS and RFID Data Using Big Data Analytics Tools in the Retail Space of the Future. Applied Sciences, 14(24), 11567–11567. https://doi.org/10.3390/app142411567

57. Kurtuluş, M., Ülkü, S., & Toktay, L. B. (2011). The Value of Collaborative Forecasting in Supply Chains. Manufacturing & Service Operations Management, 14(1), 82–98. https://doi.org/10.1287/msom.1110.0351

58. Lefouili, Y., & Madio, L. (2021). The economics of platform liability. SSRN Electronic Journal. https://doi.org/10.2139/ssrn.3791642

59. Lestari, S., & Bahri, S. (2020). Usability Web Analysis Using PSSUQ Method (Case Study on SME's Websites Application Fostered of Dispora Bandung Indonesia). International Journal of Psychosocial Rehabilitation, 24(2), 3196–3200. https://doi.org/10.37200/ijpr/v24i2/pr200627

60. Lewis, J. R., & Sauro, J. (2023). Effect of Perceived Ease of Use and Usefulness on UX and Behavioral Outcomes. International Journal of Human-Computer Interaction, 40(20), 6676. https://doi.org/10.1080/10447318.2023.2260164

61. Lichen, A. Y. (2013). Fabricating an S&OP Process: Circulating References and Matters of Concern. Research Portal Denmark, 355. https://local.forskningsportal.dk/local/dki-cgi/ws/cris-link?src=cbs&id=cbs-aad9e303-f2e7-4b4d-bee3-bdffec02895b&ti=Fabricating%20an%20S%26amp%3BOP%20Process%20%3A%20Circulating%20References%20and%20Matters%20of%20Concern

62. Lim, E. (2014). Adoption of E-Commerce in Manila.

63. Lim, G. G., & Lee, J. K. (2003). Buyer-Carts for B2B EC: The b-Cart Approach. Journal of Organizational Computing and Electronic Commerce, 13, 289–308. https://doi.org/10.1080/10919392.2003.9681165

64. Liu, Z. (2024). The Study of Users' Satisfaction and Acceptance on Artificial Intelligence (AI. Journal of Education Humanities and Social Sciences, 27, 117. https://doi.org/10.54097/f4hgqw30

65. Luca, M. (2017). Designing Online Marketplaces: Trust and Reputation Mechanisms. Innovation Policy and the Economy, 17, 77–93. https://doi.org/10.1086/688845

66. Ma, S., & Fildes, R. (2020). Retail sales forecasting with meta-learning. European Journal of Operational Research, 288(1), 111–128. https://doi.org/10.1016/j.ejor.2020.05.038

67. Macías, J. A., & Borges, C. (2023). Monitoring and forecasting usability indicators: A business intelligence approach for leveraging user-centered evaluation data. Science of Computer Programming, 234, 103077–103077. https://doi.org/10.1016/j.scico.2023.103077

68. Magrini, A. (2024). The Role of Predictive Analytics in Sales Forecasting. SSRN Electronic Journal. https://doi.org/10.2139/ssrn.5006903

69. Mentzer, J. T., Bienstock, C. C., & Kahn, K. B. (1999). Benchmarking sales forecasting management. Business Horizons, 42(3), 48–56. https://doi.org/10.1016/s0007-6813(99)80021-4

70. Mitra, A., Jain, A., Kishore, A., & Kumar, P. (2022). A Comparative Study of Demand Forecasting Models for a Multi-Channel Retail Company: A Novel Hybrid Machine Learning Approach. Operations Research Forum, 3(4). https://doi.org/10.1007/s43069-022-00166-4

71. Mitra, R., Saha, P., & Tiwari, M. K. (2023). Sales forecasting of a food and beverage company using deep clustering frameworks. International Journal of Production Research, 62(9), 3320. https://doi.org/10.1080/00207543.2023.2231098

72. Mitronen, L., & Möller, K. (2003). Management of hybrid organisations: A case study in retailing. Industrial Marketing Management, 32(5), 419. https://doi.org/10.1016/s0019-8501(03)00015-4

73. Müller, J., Würth, S., Schäffer, T., & Leyh, C. (2024). Toward a framework for determining methods of evaluation in design science research. Proceedings of the 19th Conference on Computer Science and Intelligence Systems (FedCSIS 2024) (ACSIS, 39, 231–236. https://doi.org/10.15439/2024F7208

74. Murlimanju, B. V., & Prabhu, K. R. V. (2023). 'Gantt Chart' for scheduling a scientific project. 8(2). https://doi.org/10.55889/2582-5984.1178

75. Muthers, J., & Wismer, S. (2022). Why Do Platforms Charge Proportional Fees? Commitment and Seller Participation. Review of Network Economics, 21(2), 83–110. https://doi.org/10.1515/rne-2023-0020

76. Obasuyi, F. O. T. (2025). Scholarly Writing and Educational Institution Growth Mechanism in Social Sciences: The Role of Gantt Chart in Scholarly Achievement. International Journal of Research and Innovation in Applied Science, 481–491. https://doi.org/10.51584/ijrias.2025.10020043

77. Park, H., Kim, S., Jeong, Y., & Minshall, T. (2020). Customer entrepreneurship on digital platforms:

Challenges and solutions for platform business models. Creativity and Innovation Management, 30(1), 96–115. https://doi.org/10.1111/caim.12404

78. Paura, L., & Arhipova, I. (2012). Advantages and Disadvantages of Professional and Free Software for Teaching Statistics. Information Technology and Management Science, 15(1). https://doi.org/10.2478/v10313-012-0001-z

79. Peffers, K., Tuunanen, T., Rothenberger, M. A., & Chatterjee, S. (2007). A Design Science Research Methodology for Information Systems Research. Journal of Management Information Systems, 24(3), 45–77. https://doi.org/10.2753/mis0742-1222240302

80. Pfeiffer, R. A. C. (2019). Digital Economy, Big Data and Competition Law. Market and Competition Law Review, 3(1), 53–89. https://doi.org/10.7559/mclawreview.2019.315

81. Pilar, J. G. A. (2024). Exploring Kawayan Dialect Lexicon (Wordlist) in Southern Negros, Philippines. JPI (Jurnal Pendidikan Indonesia), 13(1), 159–172. https://doi.org/10.23887/jpiundiksha.v13i1.70215

82. Pilar, J. G. A. (2025). When the Dust Settles: Miners' Lived Experiences of Survival and Transformation. https://doi.org/10.5281/ZENODO.17615960

83. Poniatowski, M., Lüttenberg, H., Beverungen, D., & Kundisch, D. (2021). Three layers of abstraction: A conceptual framework for theorizing digital multi-sided platforms. Information Systems and E-Business Management, 20(2), 257–283. https://doi.org/10.1007/s10257-021-00513-8

84. Raju, P., & Feldman, G. D. (2017). Exploiting e-commerce in construction. In Routledge eBooks (pp. 12–32). Informa. https://doi.org/10.4324/9781315690698-2

85. Rosa, A. F., Martins, A. I., Costa, V., Queirós, A., Silva, A. G., & Rocha, N. P. (2015, June 1). European Portuguese validation of the Post-Study System Usability Questionnaire (PSSUQ. 17th Iberian Conference on Information Systems and Technologies (CISTI. https://doi.org/10.1109/cisti.2015.7170431

86. Sandkuhl, K. (2023). Quantified Products: Case Studies, Features and their Design Implications. Informatica, 825–845. https://doi.org/10.15388/23-infor532

87. Saout, T., Lardeux, F., & Saubion, F. (2024). An Overview of Data Extraction From Invoices. IEEE Access, 12, 19872–19886. https://doi.org/10.1109/access.2024.3360528

88. Saputra, D. E. E., Rahma, V. M., Eliyana, A., Pratama, A. S., Anggraini, R. D., Kamil, N. L. M., & Ismail, I. (2023). Do system quality and information quality affect job performance? The mediation role of users' perceptions [Review of Do system quality and information quality affect job performance? The mediation role of users' perceptions. PLoS ONE, 18(6). https://doi.org/10.1371/journal.pone.0285293

89. Shoozan, A., & Mohamad, M. (2024). Application of Interview Protocol Refinement Framework in Systematically Developing and Refining a Semi-structured Interview Protocol. SHS Web of Conferences, 182, 4006–4006. https://doi.org/10.1051/shsconf/202418204006

90. Småros, J. (2006). Forecasting collaboration in the European grocery sector: Observations from a case study. Journal of Operations Management, 25(3), 702–716. https://doi.org/10.1016/j.jom.2006.06.005

91. Spann, M., Zeithammer, R., Bertini, M., Haruvy, E., Jap, S. D., Koenigsberg, O., Mak, V., Leszczyc, P. T. L. P., Skiera, B., & Thomas, M. (2017). Beyond Posted Prices: The Past, Present, and Future of Participative Pricing Mechanisms. Customer Needs and Solutions, 5, 121. https://doi.org/10.1007/s40547-017-0082-y

92. Stadler, M., Bannert, M., & Sailer, M. (2024). Cognitive ease at a cost: LLMs reduce mental effort but compromise depth in student scientific inquiry. Computers in Human Behavior, 160, 108386. https://doi.org/10.1016/j.chb.2024.108386

93. Staub, N., Haki, K., Aier, S., & Winter, R. (2021, January). Taxonomy of Digital Platforms: A Business Model Perspective. Proceedings of the ... Annual Hawaii International Conference on System Sciences/Proceedings of the Annual Hawaii International Conference on System Sciences. https://doi.org/10.24251/hicss.2021.744

94. Sun, Y. (2024). Sales Prediction Based on Machine Learning Approach. In Advances in economics, business and management research/Advances in

Economics, Business and Management Research (pp. 1016–1023). Atlantis Press. https://doi.org/10.2991/978-94-6463-459-4_113

95. Suresh, B. S., & Suresh, M. (2023). A Comprehensive Analysis of Retail Sales Forecasting Using Machine Learning and Deep Learning Methods. 1–5. https://doi.org/10.1109/icdsns58469.2023.10245887

96. Syahrozad, N. F., & Subriadi, A. P. (2024). Evaluation of user experience: A systematic literature review. E3S Web of Conferences, 501. https://doi.org/10.1051/e3sconf/202450102009

97. Theodorou, E., Wang, S., Kang, Y., Spiliotis, E., Makridakis, S., & Assimakopoulos, V. (2021). Exploring the representativeness of the M5 competition data. International Journal of Forecasting, 38(4), 1500–1506. https://doi.org/10.1016/j.ijforecast.2021.07.006

98. Thu, A. S., & Cho, A. (2019). Applied SPSS for Data Forecasting of Sale Quantity. International Journal of Trend in Scientific Research and Development. https://www.ijtsrd.com/papers/ijtsrd26378.pdf

99. Todorova, S. (2019). Statistics for Data Analysis Using Microsoft Excel. Izvestia Journal of the Union of Scientists - Varna Economic Sciences Series, 8(2), 68–74. https://doi.org/10.36997/ijusv-ess/2019.8.2.68

100. Tong, C. (2025). An Efficient Intelligent Semi-Automated Warehouse Inventory Stocktaking System. Operations and Supply Chain Management An International Journal, 223–239. https://doi.org/10.31387/oscm0610469

101. Xu, S. (2023). Comparison of Sales Prediction in Conventional Insights and Machine Learning Perspective. BCP Business & Management, 38, 1681–1689. https://doi.org/10.54691/bcpbm.v38i.3952

102. Yang, H., & Yoo, Y. (2003). It’s all about attitude: Revisiting the technology acceptance model. Decision Support Systems, 38(1), 19. https://doi.org/10.1016/s0167-9236(03)00062-9

103. Zhang, J. (2023). Sales Prediction of Walmart Based on Regression Models. In Advances in economics, business and management research/Advances in Economics, Business and Management Research (p. 411). Atlantis Press. https://doi.org/10.2991/978-94-6463-298-9_45

104. Zuboff, S. (2015). Big other: Surveillance capitalism and the prospects of an information civilization. Journal of Information Technology, 30(1), 75–89. https://doi.org/10.1057/jit.2015.5