

Article

Applied Sales Predictive Analytics for Business Development

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Abstract. In the dynamic business environment, leveraging predictive analytics for sales optimization and business development has become crucial for achieving sustained growth. As the e-commerce landscape continues to evolve, many e-businesses must harness the power of predictive analytics to anticipate sales trends and optimize business development strategies. This paper explores the application of sales predictive analytics, focusing on its role in forecasting sales, optimizing resource allocation, and enhancing customer relationship management. The application of predictive analytics in sales forecasting in online marketplace platforms is also explored, through the examination of various predictive models using real-world case studies. By exploring various methodologies and tools, the study illustrates how predictive analytics can be integrated into e-businesses' operations to drive growth, and enhance decision-making, highlighting the transformative potential of analytics in making data-driven decisions, ultimately fostering sustainable growth and competitive advantage. Through the analysis of historical sales data, consumer behaviour patterns, and market trends, predictive analytics provides actionable insights that are crucial for strategic planning and operational efficiency. The paper also addresses challenges and best practices for implementing predictive analytics into the business process of e-businesses.

JEL: L810, D110, D111.

Keywords: Sales process automation; Customer journey analytics; Attrition modelling; Sales trend analysis; Lead scoring.

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Introduction

In the dynamic landscape of e-commerce, businesses are increasingly leveraging advanced technologies to gain a competitive edge and optimize their operations. One such transformative technology is *Applied Sales Predictive Analytics*, which utilizes data mining, machine learning, and statistical techniques to forecast future sales trends and inform strategic business development decisions. This approach is particularly vital in the e-commerce sector, where rapid changes in consumer behaviour and market conditions demand agile and informed decision-making.

Predictive analytics in sales involves analysing historical data to predict future outcomes, thus enabling businesses to anticipate market demands, optimize inventory levels, and tailor marketing efforts to customer preferences [1]. By integrating predictive models into their business strategies, e-commerce companies can not only enhance their sales forecasting accuracy but also improve customer satisfaction and operational efficiency. This predictive capability is crucial in managing the complex and fast-paced environment of online retail, where the ability to foresee market trends can significantly impact a company's profitability and market position [2]. One of the core components of applied sales predictive analytics is the utilization of machine learning algorithms to identify patterns and correlations within vast datasets. These algorithms can analyse variables such as past sales performance, seasonal trends, customer demographics, and online behaviour to generate predictive insights [3]. For instance, through predictive modelling, an e-commerce platform can forecast peak shopping periods and adjust its inventory and staffing accordingly, thereby reducing the risks of stockouts or overstocking.

Furthermore, predictive analytics enhances personalized marketing strategies by predicting individual customer preferences and purchasing behaviours. By analysing data on customer interactions and purchase histories, businesses can create targeted marketing campaigns that are more likely to resonate with their audience and drive sales [4]. This personalization not only boosts conversion rates but

also fosters customer loyalty, as consumers are more likely to engage with brands that understand and cater to their specific needs.

The implementation of predictive analytics in e-commerce also contributes to more effective pricing strategies. Dynamic pricing models, powered by predictive analytics, can adjust prices in real time based on factors such as demand fluctuations, competitor pricing, and market trends [5]. This capability ensures that e-commerce businesses remain competitive while maximizing their profit margins.

Applied sales predictive analytics offers substantial benefits for business development in the e-commerce sector. By leveraging advanced data analysis techniques, e-commerce companies can make informed decisions that enhance sales forecasting, inventory management, personalized marketing, and pricing strategies. As the e-commerce industry continues to evolve, the adoption of predictive analytics will be essential for businesses seeking to maintain a competitive edge and achieve sustainable growth.

Sales predictive analytics leverages historical sales data, customer behaviour data, and various statistical and machine learning techniques to forecast future sales trends and customer behaviours. This approach can significantly enhance business development strategies, optimize marketing efforts, and improve customer retention.

The case used for the study is *Vinted*, an online marketplace for second-hand clothing, whereby the analysis and study conducted on predictive analytics provides valuable insights on how it drives sales performance and operational efficiency for business development.

The aim of the research is applied sales predictive analytics for business development of e-commerce companies. To fulfil the aim the following objectives were set as follow.

1. To analyse how predictive analytics is used as key drivers of sales performance for *Vinted*.
2. To determine how predictive analytics is used to segment customers based on purchasing behaviour and engagement metrics.
3. To evaluate the application of predictive analytics smart tools to predict consumer behaviour, develop effective retention strategies

optimize marketing campaigns and measure their effectiveness using the case of *Vinted*.

The scope of the research is limited as the utilization of *Vinted's* historical sales data, customer interaction data, and marketing data was applied using content analysis to build and evaluate predictive models. Other potential limitations include data privacy concerns, the dynamic nature of online marketplaces, and biases in historical data extracted from the case company.

1. Conceptual Framework of Applied Sales Predictive Analytics

The integration of predictive analytics into sales strategies have enabled organizations to move from reactive to proactive management, thereby optimizing their operations and achieving better business outcomes. In the rapidly evolving field of e-commerce, the ability to predict future sales accurately can offer a significant competitive advantage.

Applied sales predictive analytics leverages data mining, statistical analysis, and machine learning to forecast sales trends, optimize inventory, enhance marketing efforts, and ultimately drive business development. This literature review examines the current state of research on applied sales predictive analytics, focusing on its applications, methodologies, benefits, and challenges within the e-commerce sector.

1.1. Applications of Predictive Analytics in E-commerce

Predictive analytics in e-commerce encompasses various applications, from sales forecasting to personalized marketing and inventory management. Davenport and Harris [2] highlight those predictive analytics enables e-commerce businesses to anticipate market trends and customer behaviours, thus allowing for proactive rather than reactive strategies. Specifically, sales forecasting helps businesses manage supply chains more effectively by predicting demand fluctuations and adjusting inventory levels accordingly [1].

Another critical application is personalized marketing. By analysing historical data on customer behaviour, predictive models can identify purchasing patterns and preferences, facilitating targeted marketing campaigns [3]. Hazen et al. [4] emphasize that such personalization can significantly enhance customer engagement and loyalty, as customers receive more relevant product recommendations and offers.

Dynamic pricing, a strategy enabled by predictive analytics, adjusts prices in real time based on various factors, including demand, competition, and market conditions [5]. This approach helps e-commerce businesses maximize profits while maintaining competitiveness.

1.2. Methodologies in Predictive Analytics

The methodologies used in predictive analytics are diverse and complex, often involving advanced statistical techniques and machine learning algorithms. Machine learning models such as decision trees, random forests, and neural networks are commonly employed to analyse large datasets and identify patterns [6]. Linear regression and time series analysis are traditional statistical methods used for sales forecasting. These models predict future sales based on historical data trends and seasonality. However, machine learning approaches, such as supervised learning algorithms, have gained pop-

ularity due to their ability to handle more complex data structures and provide more accurate predictions [7].

Natural language processing (NLP) is another methodology used to analyse textual data, such as customer reviews and social media posts. NLP can extract valuable insights about customer sentiment and preferences, which can then inform predictive models [8].

1.3. Benefits of Predictive Analytics for E-commerce

The implementation of predictive analytics in e-commerce offers numerous benefits, including improved sales forecasting, enhanced customer experiences, and optimized operations. According to Davenport and Harris [2], businesses that leverage predictive analytics can achieve a more accurate understanding of future demand, leading to better inventory management and reduced stockouts or over-stock situations.

Personalized marketing efforts, driven by predictive analytics, result in higher conversion rates and increased customer loyalty. Hazen et al. [4] note that when customers receive personalized recommendations and offers, they are more likely to make repeat purchases and develop a stronger affinity for the brand.

Dynamic pricing models, informed by predictive analytics, enable businesses to adjust prices based on real-time data, thereby maximizing revenue, and maintaining a competitive edge [5]. This adaptability is particularly crucial in the highly competitive e-commerce market, where price fluctuations are frequent.

1.4. Challenges in Implementing Predictive Analytics

Despite its benefits, the implementation of predictive analytics in e-commerce is not without challenges. One of the primary obstacles is data quality. Predictive models rely on high-quality, accurate data to generate reliable forecasts [4]. Inaccurate or incomplete data can lead to erroneous predictions and suboptimal business decisions.

Another challenge is the complexity of integrating predictive analytics into existing business processes. Many e-commerce companies may lack the technical expertise required to develop and maintain predictive models [3]. Additionally, the rapid pace of technological change means that models need to be continuously updated and refined to remain effective.

Privacy concerns also pose a significant challenge. The use of customer data for predictive analytics must comply with data protection regulations, such as the General Data Protection Regulation (GDPR) in the European Union. Businesses must ensure that their data practices are transparent, and that customer privacy is protected [5].

1.5. Summary

The field of predictive analytics is continually evolving, with new methodologies and applications emerging. One promising area of innovation is the use of artificial intelligence (AI) and deep learning to enhance predictive models. These advanced techniques can analyse more complex data and provide more accurate predictions [9].

Another emerging trend is the use of predictive analytics in conjunction with the Internet of Things (IoT). IoT devices generate vast

amounts of data that can be used to inform predictive models, providing real-time insights into customer behaviour and operational efficiency [10].

Blockchain technology also holds potential for enhancing predictive analytics in e-commerce. By providing a secure and transparent way to record transactions, blockchain can improve data quality and trust, which are crucial for effective predictive modelling [11].

In concluding and summarising the main themes discussed, applied sales predictive analytics offers significant opportunities for business development in the e-commerce sector. By leveraging advanced data analysis techniques, e-commerce companies can make more informed decisions, enhance customer experiences, and optimize operations. However, the successful implementation of predictive analytics requires high-quality data, technical expertise, and compliance with data protection regulations. As the field continues to evolve, innovations such as AI, IoT, and blockchain hold promise for further enhancing the capabilities and applications of predictive analytics in e-commerce.

2. Research Methodology

2.1. Case Studies and Practical Applications

Several case studies illustrate the successful application of predictive analytics in e-commerce. For instance, *Amazon* uses predictive analytics to recommend products to customers based on their browsing and purchase history. This personalized approach has significantly contributed to *Amazon's* success by enhancing the customer shopping experience and increasing sales [2]. Another example is *Netflix*, which uses predictive analytics to recommend movies and TV shows to its users. By analysing viewing habits and preferences, *Netflix* can offer highly personalized recommendations, leading to higher user engagement and retention rates [3]. In the fashion industry, companies like *Zara* use predictive analytics to forecast fashion trends and optimize inventory levels. By predicting which styles will be popular, *Zara* can adjust its supply chain, accordingly, ensuring that it has the right products available at the right time [1]. The foundation of predictive analytics lies in robust data collection.

Using *Vinted*, a leading online marketplace for second-hand fashion, as the case for this research the role of predictive analytics in the business development of that company will be explored. The benefits and challenges of implementing predictive analytics, and specific applications within *Vinted's* operational framework will be examined to provide a comprehensive understanding of how predictive analytics can drive *Vinted's* growth and competitive advantage.

2.2. Research Design and Data Collection Methods

The longitudinal study design will be employed, leveraging historical data from *Vinted's* database. This approach allows for the assessment of trends, seasonality, and the long-term impact of predictive analytics models. The data sources for the research included *Vinted's* Transaction Data, Customer Data, Marketing Data and Operational Data.

The data collection process entailed extracting data from *Vinted's* CRM and ERP systems, ensuring it covers a comprehensive time frame (e.g., the past five years) and involved gathering data from various sources such as the company's sales records, and market trends. Data must be cleaned and pre-processed to ensure accuracy and consistency [12]. Data preparation steps include handling missing values, normalizing data, and ensuring data consistency across

different sources. For *Vinted*, the first step in applying predictive analytics is collecting comprehensive data from various sources, including user interactions, transaction records, and external market data. This data must be cleaned and pre-processed to ensure it is accurate and consistent. Techniques such as data normalization, missing value imputation, and outlier detection are crucial in this phase [13-14].

2.3. Research Aim, Objectives, Scope, and Limitations

The aim is applied sales predictive analytics for business development of e-commerce companies and the following objectives were set for the research:

1. To analyse how predictive analytics is used as key drivers of sales performance for *Vinted*.
2. To determine how predictive analytics is used to segment customers based on purchasing behaviour and engagement metrics.
3. To evaluate the application of predictive analytics smart tools to predict consumer behaviour, develop effective retention strategies optimize marketing campaigns and measure their effectiveness using the case of *Vinted*.

The research scope is limited due to the utilization of the company's data to build and evaluate predictive models. Other potential limitations include data privacy concerns, the dynamic nature of online marketplaces, and biases in historical data extracted.

2.4. Results and Findings

Selecting the appropriate predictive model is essential for achieving accurate forecasts. Common models include linear regression, decision trees, random forests, and neural networks. The choice of model depends on the specific business question, the nature of the data, and the desired accuracy [15].

Once the model is selected, it is trained on historical data and validated using techniques such as cross-validation and holdout samples. Performance metrics such as mean absolute error (MAE), root mean square error (RMSE), and R-squared are used to evaluate the model's accuracy. Continuous monitoring and refinement are necessary to ensure the model remains relevant as market conditions change [16].

3. Discussions

Vinted, founded in 2008, has grown to become one of the largest online marketplaces for second-hand fashion. With millions of users across multiple countries, *Vinted's* success relies on its ability to provide a seamless and efficient shopping experience. To support its rapid growth and improve operational efficiency, *Vinted* decided to implement predictive analytics. *Vinted* began by assembling a team of data scientists and engineers to develop and deploy predictive models. The team collected data from various sources, including user interactions, transaction histories, and external market data. They selected a combination of machine learning algorithms, including random forests and neural networks, to build models for sales forecasting, customer segmentation, and pricing optimization. The implementation of predictive analytics at *Vinted* yielded significant results. Sales forecasts became more accurate, leading to better inventory management and reduced stockouts. Personalized marketing campaigns resulted in higher engagement and conversion rates. Dynamic pricing strategies helped maximize revenue, while

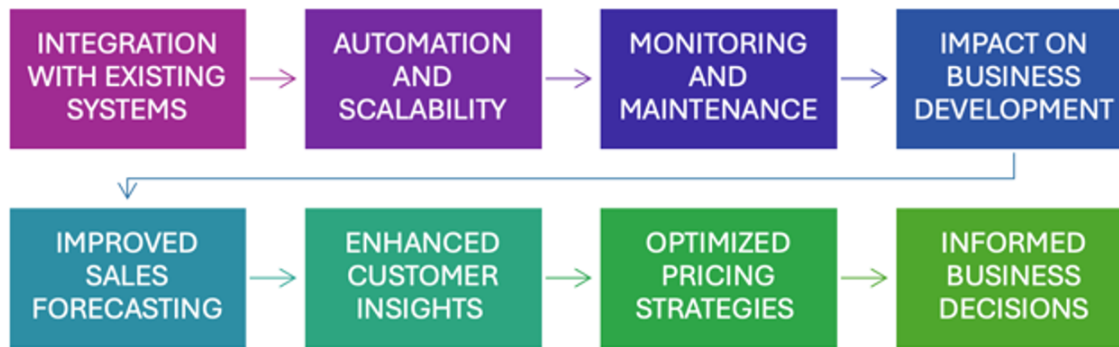


Fig. 1. Implementation process steps. Constructed according data of Refs. [17-19].

fraud detection models reduced the incidence of fraudulent transactions. Overall, predictive analytics contributed to a more efficient and profitable business operation. Predictive analytics method was applied as it uses historical data, statistical algorithms, and machine learning techniques to forecast future outcomes. In sales, it is used for forecasting sales, understanding customer behaviour, and optimizing marketing strategies. Implementing predictive analytics at *Vinted* involves integrating predictive models into the company's existing infrastructure and processes. The following steps outline the implementation process as presented in Fig. 1.

Sales Forecasting. One of the primary applications of predictive analytics at *Vinted* is sales forecasting. By analysing historical sales data and incorporating factors such as seasonality, promotions, and market trends, *Vinted* can predict future sales volumes with high accuracy. This allows for better inventory management, reducing the risk of overstocking or stockouts, and ensuring timely fulfilment of customer orders [17]. Customer Segmentation and Personalization: Predictive analytics enables *Vinted* to segment its customer base more effectively and personalize marketing efforts. By identifying patterns in customer behaviour, such as purchase frequency and product preferences, *Vinted* can tailor its marketing campaigns to target specific segments with personalized offers and recommendations. This not only enhances customer satisfaction but also increases conversion rates and customer loyalty [18].

Pricing Optimization. Dynamic pricing strategies powered by predictive analytics can help *Vinted* maximize its revenue. By analysing factors such as demand elasticity, competitor pricing, and inventory levels, *Vinted* can adjust prices in real-time to optimize sales and profitability. Machine learning models can continuously learn and adapt to changing market conditions, ensuring that pricing strategies remain competitive and effective [19].

Fraud Detection and Prevention. Predictive analytics can also play a crucial role in detecting and preventing fraudulent activities on *Vinted's* platform. By analysing transaction patterns and user behaviour, predictive models can identify anomalies that may indicate fraudulent activity. Early detection allows *Vinted* to take proactive measures to prevent fraud, protecting both buyers and sellers and maintaining the platform's integrity [20-21]. Complex models, such as deep learning algorithms, may require significant computational resources and expertise. Simplifying models without compromising accuracy can help address this challenge. It is also essential to ensure that the models are interpretable and that stakeholders understand their outputs. Interpretable models are essential for gaining the trust from stakeholders. Techniques such as decision trees and linear regression provide interpretable predictions, while advanced

methods like neural networks may require additional tools for interpretation. Explaining model decisions to non-technical stakeholders is crucial for gaining their buy-in. Handling customer data requires strict adherence to privacy and security regulations. Ensuring data protection and compliance with regulations such as the General Data Protection Regulation (GDPR) is essential. *Vinted* must implement robust security measures to protect customer data from unauthorized access and breaches.

Predictive models need to be continuously updated and improved to remain effective. Implementing a feedback loop that incorporates new data and adjusts models accordingly is a best practice. Regularly reviewing and refining models based on their performance can help maintain their accuracy and relevance. Predictive analytics has the potential to significantly enhance sales forecasting and business development for *Vinted*. By leveraging historical sales data, customer behavior patterns, and market trends, predictive models can provide valuable insights that drive informed decision-making. The successful implementation of predictive analytics requires careful integration with existing systems, automation for scalability, continuous monitoring, and adherence to best practices in data quality, interpretability, privacy, and security. Ultimately, predictive analytics can help *Vinted* improve sales performance, optimize inventory management, personalize customer experiences, and make data-driven business decisions that support sustainable growth.

Predictive models need to be seamlessly integrated with *Vinted's* e-commerce platform, data warehouses, and customer relationship management (CRM) systems. This integration ensures that models have real-time access to relevant data and can provide timely insights. APIs (Application Programming Interfaces) and data pipelines can facilitate the smooth flow of data between systems.

Automating the data collection, preprocessing, and model training processes is essential for scalability. *Vinted* can use tools like *Apache Kafka* for real-time data streaming and *Apache Spark* for large-scale data processing. Automation ensures that the predictive models are continuously updated with the latest data, maintaining their accuracy and relevance.

Continuous monitoring of predictive models is vital to ensure their performance remains optimal. This involves tracking key performance metrics and retraining models periodically to account for changes in data patterns. Implementing a feedback loop that incorporates new data and adjusts models accordingly is crucial for maintaining the effectiveness of predictive analytics.

Predictive analytics enables more accurate sales forecasts, therefore aiding *Vinted* to anticipate demand fluctuations and adjust inventory levels accordingly. This reduced the risks of stockouts and

overstock situations, leading to more efficient inventory management.

Analyzing customer behavior patterns with predictive analytics provided *Vinted* with valuable insights into customer preferences and buying habits. This information was used to personalize marketing campaigns, improve customer retention, and increase sales. For example, targeted promotions and personalized recommendations can be developed based on predictive insights.

Predictive models helped *Vinted* to analyze market trends and competitor pricing to recommend optimal pricing strategies. Through this strategy, *Vinted* remain competitive while maximizing profit margins. Dynamic pricing models, which adjust prices based on real-time demand and supply conditions, can be particularly effective.

Predictive analytics supports strategic decision-making by providing data-driven insights into market trends and business performance. This enabled *Vinted* to identify growth opportunities, allocate resources efficiently, and make informed investment decisions.

While predictive analytics offers significant benefits, from the research certain challenges were observed for successful implementation.

Data Quality. The accuracy of predictive models depends on the quality of the input data. Ensuring data accuracy, consistency, and completeness is crucial for reliable predictions. *Vinted* should implement robust data governance practices to maintain high data quality standards.

Model Complexity. Complex models, such as deep learning algorithms, may require significant computational resources and expertise. Simplifying models without compromising accuracy can help address this challenge. It is also essential to ensure that the models are interpretable and that stakeholders understand their outputs.

Interpretability. Interpretable models are essential for gaining the trust from stakeholders. Techniques such as decision trees and linear regression provide interpretable predictions, while advanced methods like neural networks may require additional tools for interpretation. Explaining model decisions to non-technical stakeholders is crucial for gaining their buy-in.

Privacy and Security. Handling customer data requires strict adherence to privacy and security regulations. Ensuring data protection and compliance with regulations such as the General Data Protection Regulation (GDPR) is essential. *Vinted* must implement robust security measures to protect customer data from unauthorized access and breaches.

Continuous Improvement. Predictive models need to be continuously updated and improved to remain effective. Implementing a feedback loop that incorporates new data and adjusts models accordingly is a best practice. Regularly reviewing and refining mod-

els based on their performance can help maintain their accuracy and relevance.

Conclusions

1. Applied sales predictive analytics offers significant opportunities for business development in the e-commerce sector. By leveraging advanced data analysis techniques, e-commerce companies can make more informed decisions, enhance customer experiences, and optimize operations. However, the successful implementation of predictive analytics requires high-quality data, technical expertise, and compliance with data protection regulations. As the field continues to evolve, innovations such as AI, IoT, and blockchain hold promise for further enhancing the capabilities and applications of predictive analytics in e-commerce.

2. Predictive analytics offers substantial benefits for business development by enabling more accurate sales forecasts, enhancing customer relationships, and optimizing resource allocation. Despite the challenges, the strategic implementation of predictive models can provide a competitive edge and drive sustainable growth. As data continues to grow in volume and complexity, businesses that effectively harness predictive analytics will be better positioned to thrive in the dynamic market landscape. The content analysis applied for the research provided actionable insights for *Vinted's* business development. By applying this method, the study sought to enhance an understanding and application of predictive analytics for optimizing sales strategies, improving customer engagement, and driving operational efficiency for *Vinted*. The insights can help *Vinted* make data-driven decisions, ultimately contributing to its growth and success in the competitive online marketplace.

3. Predictive analytics has proven to be a powerful tool for enhancing business development at *Vinted*. By leveraging data-driven insights, *Vinted* has improved sales forecasting, optimized pricing strategies, and enhanced customer segmentation. While the implementation of predictive analytics comes with challenges, the benefits far outweigh the costs. As *Vinted* continues to grow, predictive analytics will play an increasingly important role in driving its business development and maintaining its competitive edge.

Abbreviations

AI	-	Artificial Intelligence
APIs	-	Application Programming Interfaces
CRM	-	Customer Relationship Management
GDPR	-	General Data Protection Regulation
IoT	-	Internet of Things
MAE	-	mean absolute error
NLP	-	Natural Language Processing
RMSE	-	root mean square error

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