An-Najah National University
Faculty of Graduate Studies

A BUSINESS INTELLIGENCE–DRIVEN FRAMEWORK FOR ANALYZING ONLINE CONSUMER BEHAVIOR: A SIMULATION-BASED APPLICATION IN THE PALESTINIAN MARKET CONTEXT

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Dedication

"Praise be to Allah, by whose grace good deeds are accomplished"

I dedicate this achievement to my mother and father who prayed for me, to my husband Ala'a who supported me and stood by my side, to everyone who inspired me and believed in my abilities, and to my family for their patience, encouragement, and continuous inspiration throughout this academic journey.

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Declaration

I, the undersigned, declare that I submitted the thesis entitled:

A BUSINESS INTELLIGENCE–DRIVEN FRAMEWORK FOR ANALYZING ONLINE CONSUMER BEHAVIOR: A SIMULATION-BASED APPLICATION IN THE PALESTINIAN MARKET CONTEXT

I declare that the work provided in this thesis, unless otherwise referenced, is the researcher’s own work, and has not been submitted elsewhere for any other degree or qualification.

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A BUSINESS INTELLIGENCE–DRIVEN FRAMEWORK FOR ANALYZING ONLINE CONSUMER BEHAVIOR: A SIMULATION-BASED APPLICATION IN THE PALESTINIAN MARKET CONTEXT

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Abstract

The study examined Palestinian e-commerce to understand online consumer behavior after purchase by analyzing order cancellations and product returns through a business intelligence analytical framework. The research developed a synthetic dataset which uses theoretical rules to simulate local business operations because the desire was to create a dataset of actual transaction records but lacked access to real transaction data. The study used descriptive diagnostics along with supervised machine-learning models to determine order outcomes and identify key risk factors. The study found that delivery lead time has the highest impact on both order cancellations and product returns while payment method and order value and customer purchasing behavior follow as secondary factors. The ensemble and probabilistic models deliver dependable results which can be easily understood making them ideal for decision-making in markets that lack sufficient data. The research demonstrates that synthetic data, which has undergone analytical validation, combined with business intelligence and predictive analytics, produces practical insights that help e-commerce businesses manage their operations and post-purchase risks in developing countries.

Keywords: Business Intelligence. Synthetic Data. Simulated data. Online Consumer Behavior. E-commerce. Machine Learning. Post-purchase Behavior. Order Return Prediction. Palestinian Market.

Chapter One

Introduction

1.1 Contextual and Analytical Background

The rapid expansion of the digital economy has reshaped consumer purchasing behavior worldwide, with online shopping becoming a central mode of consumptions across multiple market and demographic segment (Aish & Noor, 2025; Haddara et al., 2023). Global e-commerce growth has been driven by advances in digital infrastructure, payment system, logistics, and social media, which together enable continuous online access, broader product assortments, and data-driven personalization at scale (Aish & Noor, 2025). At the same time, the rise of platform economies and artificial intelligence–based recommendation systems mean that online retailers increasingly rely on large-scale behavioral data and predictive analytics to understand and influence consumer decision (Stylianou & Pantelidou, 2025a).

In Palestine, access to the digital economy is develop within a highly constrained political and infrastructural environments, where occupation-related restriction of movement, trade, spectrum allocation, and postal systems limits the ability of individual and firms to fully participate on e-commerce (Abudaka & Taha, 2019). Despite this structural barriers, empirical evidence show that Palestinian in the West Bank and Gaza are increasingly engaging with online shaping, using social media page, local platforms, and international marketplace for buy and sell products (Aish & Noor, 2025). However, this participation are uneven and fragile because of logistical bottlenecks, long delivery times, and additional cost associated with routing goods and payment through Israeli-controlled systems and third-country intermediaries (Abudaka & Taha, 2019). As a result, e-commerce in Palestine simultaneously represents a mechanism to economic inclusion and a site where digital discrimination, infrastructural weaknesses, and regulatory gaps are reproduce.

Broader assessments of “e-commerce readiness” in Palestine further underline how consumer behavior online is constrained by macro-level condition related to digital access, financial inclusion, logistics, and legal frameworks (Abudaka & Taha, 2019). Internet and mobile using has increased fast, with majority of household connect and high level of social media uses, However, broadband quality, mobile broadband deployment, and digital skills remain uneven across regions and income groups. (Abudaka & Taha, 2019). Financial inclusion is comparatively low, with limited credit card usage, heavy reliance on cash, and restricted access to major global payment gateways like PayPal, which collectively enhance cash-on-delivery as the dominant payment methods and heighten perceived transaction risks (Abudaka & Taha, 2019). Logistic and postal systems is also underdeveloped, with international shipment to West Bank and Gaza routed by Israel infrastructure, generating long delay, uncertainty, and additional cost that reduces both consumer confidence and merchant competitiveness (Abudaka & Taha, 2019). This constraints means that Palestinian consumers' online shopping decision are not shaped by individual attitudes and technology perceptions only but also by structural barriers on payment, delivery, and regulation (Aish & Noor, 2025).

At same time, regulatory development like the General Data Protection Regulation illustrate that data-driven e-commerce has to operate under evolving privacy, consent, and data-protection regime, which have direct implication to analytic practices and consumers trust (Haddara et al., 2023). Studies from European market show that GDPR compliance initially increased cost and reduce some forms of tracking and website traffic, yet also strengthened data security, clarified consent processes, and ultimately contributed for higher levels of customer trust and more disciplined data governance (Haddara et al., 2023). In e-commerce firm, the regulation have lead to stricter limitation on the scope of personal data collected, more explicit informed-consent mechanism, and closer integration between legal, IT, and analytics functions in designing and operating business intelligence system (Haddara et al., 2023). These finding underlines that advanced analytic and business intelligence on online shopping environments is inseparable from trust-building, transparency, and regulatory alignment, especially when predictive model rely on sensitive behavior and transactional data (Aish & Noor, 2025). Note that this study do not process real personal data, but draws conceptual implications for analytics governance.

Against this backdrop, the Palestinians online shopping context are marked by a dual gap that justify a focused BI-oriented analysis of consumers behavior (Aish & Noor, 2025). First, existing Palestinian and region studies tends to analyze online shopping behavior using survey-based structural model, without leverage transactional or interaction-level data for build predictive or segmentational models tailored to local condition (Aish &

Noor, 2025). Second, most advanced BI and machine-learning application of e-commerce are developed with stable, highly digitized market, with little attention to settings characterized by political instability, limited payment and logistic options, and pronounced trust deficit (Haddara et al., 2023). Bridging these gap require integrating the behavioral constructs identified of Palestinian studies—digital marketing practices, e-word of mouth, trust, and persuasion knowledge—with data-driven technique like predictive modeling, clustering, and association analysis, in order to capture both attitudinal and behavioral dimension of online shopping. Consequently, recent methodological literature support the use of synthetic data generation as a scientifically valid alternatives for simulating realistic consumers behavior patterns when real data is inaccessible, provided that the data generation processes is theoretically grounded and analytically validated (Sanchez-Serrano et al., 2025).

Accordingly, this study position business intelligence–driven analysis as suitable and necessary approach to examining online consumer behavior of the Palestinian context. By integrating theoretically grounded synthetic data generation with advanced descriptive and predictive analytic, the study overcome limitations in data availability while enable systematic examination of order status patterns, thereby providing empirically informed insights for support operational and strategic decision-making in e-commerce environments.

1.2 Theoretical Basis

1.2.1 Behavioral Decision Theory as the Core Theoretical Lens

Behavioral Decision Theory (BDT) represent the primary theoretical foundation of this study by conceptualize consumer as limitedly rational decision-makers who navigate complex trade-offs under constraint (Dominic & Pardamean, 2023). On this frameworks, consumer choice are shaped by evaluation of quantifiable risk and non-quantifiable sources of uncertainty that associated with available resource and alternative outcomes (Sun & Chen, 2025). Online shopping decisions—particularly these related to payment choices, order cancellation, and product returns—is made under condition of imperfect information and heigh perceived financially risks (Li et al., 2023). These outcome represent risk-evaluation tasks on which consumers weigh expected purchase utility against anticipated “return hasle cost” related of time, effort, and uncertainty (Sun & Chen, 2025).

The e-commerce environment experience higher decision-making challenges in Palestine because of their regular delivery delays which restrict payment options and creates continuing trust issues (Aish & Noor, 2025). Political instability, weak consumer protection mechanism, and fragment logistic amplify uncertainty regarding products authenticity and orders fulfillment, while underdeveloped infrastructure further complicate the rational assessment of potential transaction loss (Awad et al., 2021). Although intention-based model like UTAUT focus on consumers’ willingness for adopt digital technologies, they largely overlook ex-post friction that frequently trigger transaction failure (Belmonte et al., 2024).

According to that, Behavioral Decision Theory provide more suitable analytical lens to examining observed transactional outcome, as it explicitly account for how external constraints and risk perceptions systematically reshapes consumers behavior (Dominic & Pardamean, 2023). This perspective offer stronger explanatory and diagnostic power to understanding why cancellation and returns emerge as rational adaptive response in volatile digital marketplace.

1.2.2 Theory of Planned Behavior as a Supporting Explanatory Framework

The analysis of online consumer behavior are based in several well establish theoretical frameworks that explains technology adopting and behavioral intention. Among those, the Theory of Planned Behavior (TPB) suppose that behavioral intention is determined by attitudes, subjective norms, and perceived behavioral control. Empirical application of TPB in e-commerce research demonstrate its robust explanatory power of predicting online purchase intentions, especially for digitally mediate products and services (Kozik et al., 2024).

1.2.3 Technology Acceptance Models (TAM & UTAUT2) in the E-Commerce Context

Technology Acceptance Model (TAM) had been extensively employed for explain users’ adoptions of online systems. TAM emphasize perceived usefulness and perceived easy of use as primary antecedent of technology acceptance. In e-commerce context, those constructs had been shown to significantly influence consumers’ attitudes and purchase intention, particularly when extended to includes trust and enjoyment variables (Singh et al., 2024).

The evolution of digital shopping environment have led to the extension of traditional acceptance model, like UTAUT2, which incorporate hedonic motivation, perceived value, and habitual behavior. Empirical finding indicate that those constructs plays a critical role in explaining consumers' preference for online shopping over physical retail, particularly on the post-pandemic period (Higueras-Castillo et al., 2023).

1.2.4 Trust and Perceived Risk in Online Consumer Decision-Making

Trust-based theories occupies a central position on online consumers behavior research. Trust functions as mediating mechanism between platform characteristics—like security, information quality, and service reliability—and purchase intention. Empirical evidence confirm that trust significantly influence initial purchase decisions and long-term customer loyalty on online shopping environments (Mofokeng, 2023).

In this stream, trust- and risk-based models provides second pillar of the theoretical foundation by explain how perceptions of website reliability and transaction risk condition purchase and post-purchase behavior. Trust-based consumer decision model on electronic commerce show that trust on an online seller and perceived risk significantly affects the decision for purchase, with trust shaped by factors like vendor reputation, information quality, and privacy and security assurance. Empirical research on consumer trust and perceived risk on e-commerce confirm that higher vendor and product brand equity increase perceived trust, reduce perceived risk, and enhance willingness for transact, highlighting the central role of trust-building mechanisms on digital markets. Those models imply that when perceived risk remain high or trust is undermined after the transaction—for example because poor logistics or service failures—customers maybe react through complaints, returns, or order cancellations as forms of post-purchase behaviors.

1.2.5 Post-Purchase Decision Models and Return Behavior

Literature on returns and cancellations on e-commerce show group of operational and policy-relating factors that shapes post-purchase behavior. Work on digital purchase and online retailing show that delivery time reliability, return policy leniency, information quality, and customers service quality influences satisfaction and engagement, which on turn affect the probability of complaints, returns, and relationship termination (Donker et al., 2025). Studies focus on e-commerce website factors observes that return policies, cost-saving opportunities, product variety, and perceived convenience influence consumer trust and purchasing intention, implying that unfavorable delivery condition or restrictive return policies can increases return and cancellation behavior (Sun & Chen, 2025). Also, evidence from online order satisfaction and pricing research indicate that discounts, pricing strategies, payment method flexibility, and perceived transactions security shape expectations and satisfactions, so impacting the propensity for cancel orders or initiate returns when expectations are not met (Lu et al., 2025).

Complementing those theoretical models, machine learning–based predictive frameworks demonstrated superior capabilities on capturing complex, non-linear consumer behavior patterns. Integrating theoretical constructs with predictive analytics enable more comprehensive understanding to online purchase intention through combine explanation and predictions (Stylianou & Pantelidou, 2025a).

1.2.6 Business Intelligence and Predictive Analytics as an Analytical Framework

The analytical lens of business intelligence (BI) provide supplementary theoretical basis by link operational data with strategic decision-making about consumer behavior, returns, and cancellations (Alabi et al., 2022). BI and predictive analytics approaches on online retail use transaction histories, behavioral clickstream data, and lagged order indicators to modeling satisfaction, predict return or cancellation statuses, and segment customers according to risk of churning or complaint (X. Chen, 2025). Through data warehousing and advanced analytic, BI system transform dispersed operational indicator—like delivery performance, payment behavior, and promotion response—to actionable knowledge that supports strategic decisions on services design, risk management, and customers relationship policies (Shen et al., 2020). In the context of this study, simulation-based BI model enable the testing of alternative policy scenarios (e.g., different return-window lengths, shipping options, or discount strategies) and its expected impact on predicted returns and cancellations, and so aligning operational configurations with strategic objectives on the Palestinians e-commerce environment.

1.3 Problem Statement

The core problem addressed of this study lies in the absence of structured, data-driven analytical framework designed to data-constrained market that can effectively analyze and predict online order cancellation and return behaviors. This study addresses this gap through employ business intelligence–driven analysis supported by theoretically ground synthetic data, enable the development and evaluation of predictive models which generate actionable insights to improving decision-making in Palestinian e-commerce contexts.

1.4 Research Questions

RQ1. What transactional and operational factors are most strongly associated to online order cancellation and return behaviors, based on descriptive and predictive analytics?

RQ2. To what extent can synthetically generated data, when theoretically grounded and analytically validated, represents realistic pattern on online consumer behavior in data-constrained markets like Palestine?

RQ3. How effective is business intelligence–driven predictive models of identifying and forecasting orders possible to be cancelled or returned?

RQ4. How could insights derive from descriptive and predictive analytics be operationalized with business intelligence framework for support data-driven decision-making on e-commerce operations?

1.5 Importance of the Study

Theoretical Contribution

This study contributes the literature in online consumer behavior by shift the analytical focus from purchase intention to post-purchase behavior, particularly order cancellation and return. Through examine those outcomes through operational and transactional data, the study extends existing research that has largely relied on perceptual and survey-based approaches.

Moreover, the study advances theoretical understand by positioning business intelligence and predictive analytics as complementary analytical framework to studying digital consumer behavior. The use of synthetic data further contributes methodologically by demonstrating viable research approach to data-constrained market, thus supporting future theory-driven analytical research on similar contexts.

Practical Contribution

From practical perspective, the study demonstrate how predictive models could be developed to anticipate order cancellation and return behavior before order fulfillment. This predictive capability enables e-commerce firms for identify high-risk orders early and to shifting from reactive to proactive management of post-purchase outcomes.

Additionally, integrating these predictive models with business intelligence environment transform analytical results to decision-support tools that could be actionable, like risk scoring and operation insights. This support improved inventory planning, logistics coordination, and return management, especially in emerging markets where operational efficiency is critical.

1.6 Objectives of the Study

The main objective of this study is developing data-driven analytical framework to examining and predicting online order cancellation and return behavior in Palestinian e-commerce context. Specifically, the study aims to:

1. **Design and construct synthetically generated dataset** that realistically represent transaction and operational characteristics of online consumer behavior on the Palestinian markets.
2. **Analyze transactional and operational factors** associated to order cancellation and return behavior by using descriptive and analytical techniques.
3. **Develop and evaluate predictive models** able to forecasting the likelihood of order cancellation and return based on observable transaction data.
4. **Integrate predictive and descriptive perspectives with business intelligence framework** for support data-driven operational and managerial decision-making.
5. **Demonstrate the methodological validity of synthetic data** as practical alternative to advanced analytics on data-constrained e-commerce environments.

Chapter Two

Literature Review

2.1 Consumer Behavior in the Context of E-Commerce

2.1.1 Concept and Evolution of Consumer Behavior

The rapid advancement and integration of digital technology into the global economy has established a new era widely characterized as the digital age (Handoyo, 2024). This era has facilitated a paradigm shift in the manner through which consumers interact with businesses, making the purchase of goods and services increasingly convenient (Handoyo, 2024). In the initial development stage of e-commerce, business intelligence systems primarily relied on periodic sales data and customer transaction records to formulate marketing strategies (X. Chen, 2025). Contempor social media platforms has transitioned to a artificial intelligence technological paradigm where recommendation algorithms represent as the core infrastructure for the digital economic (X. Chen, 2025). Online consumer behavior are fundamental shape by several significant factor, include trust, perceived risk, perceived security, and electronical word-of-mouth (Handoyo, 2024). Modern behavior analyses utilize deep data mining to discovering the information values in multi dimensional users behavior patterns (X. Chen, 2025). This technology evolution allow to the construction of accurate prediction models to identifying high-value customer intention and behavioral preferences (X. Chen, 2025).

2.1.2 Transition from Traditional to Online Consumer Behavior

The transition from traditional retail to electronical commerce were significant accelerated by the COVID-19 pandemic, which that acted as a catalyst to shifting consumer habit to digital channels for avoid physical contacts (Higueras-Castillo et al., 2023). This shift are basically motivated by the perceived advantage of online platforms on traditional shopping, specifically regarding convenience, time savings, and the ability to comparing a broader selection of products (Baidoun & Salem, 2024). In specific region contexts like Palestine, the purchase decision on this online environment are driven by significant behavior factors include perceived privacy, behavioral control, website quality, and subjective norms (Baidoun & Salem, 2024). The influencing of those factors are more strengthened by the moderating roles of commitment, which function as critical predictor for consistent online shopping behavior (Baidoun & Salem, 2024). Otherwise, the transition are sometimes obstructed by barriers like switching costs, perceived risk, and fear of technologic, which encourage consumers to maintaining their usage of the physical store (Higueras-Castillo et al., 2023). Comparing empirical evidences indicates that the intensity of this transition is vary by region, where Spanish consumers shows a significant higher average intention to use online channels more than Portuguese consumers (Higueras-Castillo et al., 2023). Despite those differences, the definition of consumer segments through this transition are governed more by behavioral patterns more than by socio-demographic characteristics, which generally lacks significance influence on usage intention (Higueras-Castillo et al., 2023).

2.1.3 Characteristics of Online Consumer Behavior

Online shopping behavior are characterized by psychologic state of the consumers and the cognitive processing of purchase intention (Miah et al., 2022). This behavioral follow a structured decision-making processing involve acknowledgment, information search, and the evaluation of transaction options (Miah et al., 2022). Consumer conduct on digital setting are significant influenced by variables like trust, perceived risk, perceived security, and electronic word-of-mouth (Aish & Noor, 2025). Social media platforms facility interactions that it allow users to share opinions and product knowledge, thus impact the behavior of the other consumers (Miah et al., 2022). The process of acquire and accommodate information regarding e-commerce platforms function to reducing perceived risk and foster higher consumer engagement (Aish & Noor, 2025). In specific development regions, those behavioral characters are on evolving stage and are often formed by economic instability and culture attitudes (Aish & Noor, 2025). Finally, effect participation on digital commerce are dependent on digital literacy, which it involves the ability to finding and evaluating information across different digital platforms (NAZZAL et al., 2021).

2.1.4 Decision-Making Process in Online Shopping

Consumer behavior on digital environments are identified as the activity and processes that involved on purchase and ordering products based on personal experience and personal ideas (Liang & Hu, 2024). The decision-making process on social commerce are facilitated by providing consumers with enough marketer- and consumer-generated information to ease product selection (Mikalef et al., 2023). Analysis this process via eye-tracking indicates that the importance of different informational alarms, like product images and price, transform dynamical over time during the decision-making journey (Mikalef et al., 2023). Also, group decision-making on collaborative shopping context significant impact individual choices as collecting opinions evolve to a consensus (Liang & Hu, 2024).

2.1.5 How does consumer behavior manifest in observable order outcomes?

Consumer behavior on online shopping environments became empirical visible when it is translated to sequence of transaction event—clicks, basket additions, payment attempt and after purchase actions—that culminates in order outcomes, include completion, cancellation, or return (Z. Chen et al., 2023). Previous research using clickstream and order-log data that showing that pre-purchase behaviors like search breadth, number of product page view, and basket modifying frequent are systematical associate to the possibility of order completion, as they make instances of underly cognitive processes like information search, uncertain reduction, and preference formation (El Kihal et al., 2025). Studies about post-purchase data more demonstrated that delayed payment, repeated modifications of delivery options, and last-minute basket editing predict higher cancelation likelihood, which indicate that unresolve risk perceptions or low commitment at checkout tend to materialize as order abandon instead of lower stated intention (X. Chen, 2025). Instead of using survey intentions, those studies analyze real order histories and treat completion, cancellation, and return as observe behaviors that reflects underlying factors like trust, risk perception, and satisfaction—focus on what consumers actual do rather than what they say they will do (Donker et al., 2025).

2.2 Post-Purchase Behavior in Online Retail

2.2.1 What constitutes post-purchase behavior in e-commerce?

In e-commerce, the post-purchase behavior are conceptual as the set cognitive evaluation, affective response, and observe actions that occurs after the transaction were placed and extend during order fulfillment, consumption, and subsequent relational exchange with the retailers (El Kihal et al., 2025). Scholar define post-purchase outcomes along the three interrelate dimensions: operation fulfillment performance (e.g., delivery timeliness, accuracy, and condition of the received goods), evaluative states like online order satisfaction, and behavioral responds include repeat purchase, complaint, word-of-mouth, and returning (Donker et al., 2025). Operationally, the recent work in predicting online order satisfaction model post-purchase outcomes by using lag transaction indicators (delivery delays, partial shipments, prior issues) and link those to satisfaction ratings and subsequent purchase incidence, thus treating satisfaction as ex-post evaluative judgment that grounded in concrete fulfillment experiences instead of ante expectations (Le et al., 2024a). Research on e-service quality also examine post-purchase behavior via satisfaction and loyalty, by using surveys, repurchase intentions, and repeat orders. Those studies shows that reliability, responsiveness, and effective problem resolution after purchase influence customer satisfaction and was continued buy behavior on online environments (Rita et al., 2019). Thereby embedding returns and complaint handling squarely within the broader framework of post-purchase behavior in digital commerce (Mofokeng, 2023).

2.2.2 How are order cancellations and returns conceptually and operationally distinguished?

E-commerce research increase distinguishes between cancellation and returns as two different post-purchase events (El Kihal et al., 2025). Cancellations happens before shipment, between order placement and dispatch, and are usually linked to continue uncertainty, perceived risk, or changing preferences (Donker et al., 2025). In contrast, returns occurs after the product has been delivered and inspected, and are mainly driven by dissatisfaction or expectation disconfirmation (Z. Chen et al., 2023). Operationally, cancellations appears as status changes on order systems, while returns is recorded in reverse logistics systems and affect inventory and recovery decisions (Sun & Chen, 2025). Because of this difference, cancellations are usually used as indicators for checkout friction or delivery concerns, while returns is analyzed as repeated behavioral outcomes linked to customer heterogeneity or policy of bad use (Donker et al., 2025).

2.3 Determinants of Order Cancellations and Returns

2.3.1 How does delivery performance influence return and cancellation behavior?

Empirical research show that delivery performance strongly affect both of cancellations and returns, but on different ways (Donker et al., 2025). Reliable and fast delivery reducing uncertainty and lowering cancellation rates, and long or chang lead times increasing perceive risk and might cause customers to cancel before shipment (El Kihal et al., 2025). After delivery, late shipments or errors reduces satisfaction and is increasing the likelihood of returns, especially when delays reduces perceive values or when wrong or damaged items are received (Le et al., 2024a). Poor fulfillment reliability also move return reasons toward problems that related to seller, increasing operation and financial costs compare to cancellations that occurs before shipping (Donker et al., 2025).

2.3.2 How do pricing and discount strategies affect adverse order outcomes?

Research shows that pricing and discounts influencing cancellations and returns by shape how customers perceiving value at purchase and how they feel after that (Z. Chen et al., 2023). Discounts can increase sales at first, but they may also creates regret if customers finds better deals later, which can lead to cancellations (Handoyo, 2024). Deep discounts usually attracts price-sensitive customers who are more likely to returning products, especially on categories with high uncertainty, cause low prices encouraging trial purchases (Sun & Chen, 2025). However, pricing policies that designed well —like control markdown or segment-based pricing—can reduce opportunity to returns and match expectations with actual value (Donker et al., 2025). Overall, while discounts driving acquisition, their structure determine whether orders end on satisfaction or in higher cancellation and return rates (El Kihal et al., 2025).

2.3.3 How do payment methods shape post-purchase behavior in e-commerce?

Research show that payment method affect post-purchase behavior because it shape both of perceived risk and customer commitment at checkout (Aish & Noor, 2025). In emerging markets, cash on delivery (COD) reduce perceived risk by postpone payment, but it also weaken commitment, which lead to higher refusal and last-minute cancellation rates (NAZZAL et al., 2021). Digital payments, such as cards and e-wallets, requires upfront payment and is often linked to secure systems (Handoyo, 2024). When trust exist, they increase order stability and reduce cancellation risk, although dissatisfied customers might relies more on formal return procedures (Belmonte et al., 2024). Studies also shows that perceived security, ease of use, and institutional trust strengthens adoption and loyalty in digital payments, resulting in more consistent purchasing behavior compared to COD users (Belmonte et al., 2024; German Ruiz-Herrera et al., 2023). Overall, COD reduce perceive risk but it increase instability, while trusted digital payments increases commitment and it move adverse outcomes toward structured returns (Aish & Noor, 2025).

2.3.4 How does customer heterogeneity influence order outcomes?

E-commerce analytic increasing recognizes customer heterogeneity as major source of variations on post-purchase outcomes (El Kihal et al., 2025). Instead rely on attitudinal constructs, recent study segment customers by using observe transactional behavior that predicting cancellation and return tendencies (Mofokeng, 2023). Empirical research in return-rate evolution show that repeated returners form a distinct behavioral segments (Sun & Chen, 2025). Prior return behavior were shown to predicting future returns more accuracy than stated intentions or demography characteristics (Z. Chen et al., 2023). This pattern suggest that, for some customers return products become a learned and habitual behavior, in particularly under permissive return policy (El Kihal et al., 2025). Studies that applying machine learning and behavioral predicting models further indicates that loyalty status moderates order outcome stability strongly (Mofokeng, 2023). High-frequence and active customers tend to exhibits low cancellation rates (El Kihal et al., 2025). In opposite, sporadic and low-engagement customers demonstrates higher sensitivity to cancel (Sun & Chen, 2025). Its return behaviors is more volatile and often opportunity, driven by deal-seeking motive and low charging costs (Sun & Chen, 2025). Research that integrates transactional historical with contextual variable also highlight the role demographic interaction (Le et al., 2024a). Overall, literature demonstrate that heterogeneity on cancelations and return are best explain by revealed behavioral pattern. Variables like purchase frequency, return historical, baskets composition, and engage intensity outperform psychographic or attitude segmentation (Z. Chen et al., 2023). Thus, transactional trace data emerges as most reliable foundations of predictive modeling and for design segment-specific intervention strategies on e-commerce (Le et al., 2024a).

2.3.5 How do product categories influence return likelihood?

Product category basically dictate return likelihood cause of vary levels of fit uncertainty and logistic constraints (El Kihal et al., 2025). The fashion sector shows especially high return rates—often around 30%—mainly because consumers can't physical check size or fit before purchase (Sun & Chen, 2025). In contrast, bulky furniture or low-value items is returned less frequent, as high hassle cost and logistic burden discourages returns even when there are a mismatch (Sun & Chen, 2025). Research also show that experience product face higher rejection rates more than standardized goods because tactile evaluation are absent online (Z. Chen et al., 2023). In addition, specific behavioral patterns emerges when consumers purchase cross multiple categories; for example, buying complementary fashion items can actually reduces return probability by ensure aesthetic compatibility (El Kihal et al., 2025). Overall, although review and product information can reducing uncertainty, category-specific logistical constraints remains a key determinant for return behavior (Singh et al., 2024; Sun & Chen, 2025).

2.3.6 How do seasonal and promotional contexts affect order outcomes?

Season peaks and promotional events, like mega-sales festival, induces substantial operation strain in e-commerce fulfillment architecture and inventory management systems (Esmeli et al., 2022). Those period frequent result on delivery congestion, which is directly impacts fulfillment timelines and reduce perceived e-service quality (Goedhart et al., 2023; Mofokeng, 2023). Diagnostic evaluations indicate that on-time delivery serves as a primary antecedent of consumer trust, in particular in markets characterized by the high uncertainty avoidance (Mofokeng, 2023). And so, any failure to matching delivery speed with height consumer expectation during peak demand cycles escalating perceived risk and ex-post not satisfaction (Chau et al., 2025).

2.4 E-Commerce in Developing and Emerging Markets

2.4.1 Structural and Infrastructural Characteristics of E-Commerce in Developing Markets

E-commerce in developing countries are still at early stage comparing to global markets (Alyoubi, 2015). In Palestine, for example, there are a gap between high internet and smartphone accesses and actual using of online shopping (NAZZAL et al., 2021). Those markets faces structure barriers like bad internet connection, limited digital infrastructure, and not very developed logistics systems (NAZZAL et al., 2021). There are also strong rely on cash-on-delivery because of digital payment options remains limited (Shwaika & Ayyash, 2023). As a result, consumers usually faces difficulties like spend more time to searching for products and dealing with uncertainty during the purchasing process (Baidoun & Salem, 2024). Final, the digital realm on those economies are often characterized by systemic concerns regard to fraudulent transactions, delivery failures and lack of robust data privacy protections (Aish & Noor, 2025).

2.4.2 Consumer Behavior Patterns in Developing and Emerging Markets

The pattern of consumer behavior on developing countries result from three factors which interact with each other through digital literacy and institutional trust and regional sociocultural elements (Aish & Noor, 2025). The research evidence demonstrate that machine learning systems can learn successfully from those pattern because they constructed hyperscale cross-cultural datasets which enabled them to reach more than 80 percent prediction accuracy to emerging markets (X. Chen, 2025). The Palestinian Statistics Centre reports that eight percent of people on developing areas which have extensive internet access and smartphone usage still don't shop online because they lack knowledge about online transaction procedures (NAZZAL et al., 2021). The behavior persists because people keep use cash-on-delivery payment systems which result from their worries about online fraud and delivery problems and data privacy issues (Elsaeed et al., 2024). Individual purchase decisions are mostly influenced by two factors which includes subjective norms and the pressure that come from major reference groups who exist on these particular situations (Baidoun & Salem, 2024).

2.4.3 Methodological and Data-Related Challenges in Developing Markets

E-commerce businesses face challenges on data analysis because their data collection create a large imbalance between its extensive browsing record and their minimal transaction data (Zareian Beinabadi et al., 2024). The data structure contains two unequal part which create predictive bias because standard algorithms treats the main non-purchasing group as their primary training target (Z. Chen et al., 2023). In emerging markets, small and irregular datasets reduce model stability and increase classification difficulty (Tabianan et al., 2022). Limited historical data also restrict the ability to building long-term behavioral cohorts (Fedushko & Ustyianovych, 2022). The ongoing problems with processing unbalanced datasets together with discovering important consumer features continue to create obstacles for predicting online shopping behavior (Z. Chen et al., 2023).

2.5 Business Intelligence and Diagnostic Analytics in E-Commerce

2.5.1 How has diagnostic analytics been applied to analyze order outcomes?

Diagnostic analytic help explain why orders end on completion, cancellation, or return by analyzing past transaction data (Stylianou & Pantelidou, 2025a). Researchers examines patterns in key variable —like cancellations and delivery delays—to understanding what drive final order outcomes (Donker et al., 2025). Techniques like clustering and pattern analysis identifying how customer segments and product relationships affecta return and cancellation behavior (Stylianou & Pantelidou, 2025a). Empirical findings shows that a "return habit effect," where a higher share of past returns represent a non-causal indicator of future returns likelihood (El Kihal et al., 2025). Some research uses also customer reviews to explaining dissatisfaction relating to product quality or delivery performance (Le et al., 2024a). Overall, diagnostic analytics provides actionable insights that supporting better inventory planning, pricing decisions, and operational adjustments (Pawełek-Lubera et al., 2025; Stylianou & Pantelidou, 2025a).

2.5.2 How is predictive analytics used to anticipate returns and cancellations

Predictive analytics on e-commerce mainly use supervised machine-learning models to forecasting whether an order will be completed, cancelled, or returned (Esmeli et al., 2022). While advanced models are exist, simpler algorithms like Random Forest and Decision Trees are usually preferred because they are easier to interpreting and apply in practice, especially on emerging markets with limited data (Goedhart et al., 2023). Those models rely on historical transactional data and past customer behavior (El Kihal et al., 2025; Stylianou & Pantelidou, 2025a). For example, prior return behavior predicting future returns strongly, while accumulated product experiencing can reduce return likelihood over time (El Kihal et al., 2025). Order characteristics and timing provides useful predictive signals also (Esmeli et al., 2022). By treat order outcomes as the classification tasks based on the past data, predictive analytics help retailers to identifying risk patterns and support decisions based on evidence (Stylianou & Pantelidou, 2025a). The process of making models understandable to users enable its continuous operation on unpredictable online retail settings because it confirms their operational dependability. (Günther et al., 2017).

2.5.3 Shift from Survey-Based to Data-Driven Studies

Conventional research methodologies on consumer behavior has usually utilized surveys as basic instruments for collecting quantitative data (Tabianan et al., 2022). Chen (2025) states that traditional analysis models which operate on explicit consumption data face two main problems when they attempt to capture user behavior patterns and intentions through their analysis methods (X. Chen, 2025). The development of machine learning algorithms has created a new approach which uses data analysis to predict consumer behavior through its multi-dimensional feature space and active classification techniques(Shwaika & Ayyash, 2023) . The new technology streamlines high-value user identification processes while it enables e-commerce businesses to respond to market changes at faster rates than they could using traditional manual data analysis methods (Z. Chen et al., 2023).

2.6 Synthetic Data and Simulation-Based Analytics in E-Commerce Research

E-commerce data have developed from simple records to complex datasets that including many variables like user ratings, timing, and product features (Jin et al., 2024). Big data analytics help automating the processing of large volumes of information and supporting intelligent decision systems (Fedushko et al., 2020). Researchers uses big data also to analyzing specific user groups over time, improving the study of consumer behavior (Fedushko & Ustyianovych, 2022). In business intelligence systems, large datasets are used to customer segmentation and personalized marketing (Zabukovšek et al., 2020).

2.6.1 Synthetic data in e-commerce and business analytics research

Synthetic data helping solving data scarcity and class imbalance on e-commerce research (X. Chen, 2025). Generative techniques is used to increasing rare cases, like unhappy customers or returns (Donker et al., 2025). This approach are essential on emerging markets where that able to access data and quality remains significant barriers to reliable analytics (Chau et al., 2025). Researchers on those contexts often lacks long-term digital records, so the simulated data supports more accurate behavioral modeling (Chau et al., 2025). Privacy concerns limits access to real transactional data also, encourage the using of synthetic alternatives (Mofokeng, 2023). Compliance with regulations like GDPR require strict data protection practice (Bajwa et al., 2025; Belmonte et al., 2024). By using synthetic data, researchers can builds reliable predicting models without exposing private customer information and can still detects meaningful behavioral patterns (X. Chen, 2025; Stylianou & Pantelidou, 2025a).

2.6.2 Applying simulation-based approaches to model e-commerce transactions

Simulation-based, rule-driven data generation are widely used on e-commerce research to creating realistic transaction datasets when accessing to real data is limited by confidentiality or scarcity (Bajwa et al., 2025). It create realistic datasets by using probability rule and logical constraints—for example, allow returns only after delivery—to maintaining behavioral and temporal consistency (Donker et al., 2025). Rule-based simulation are particularly effective for modeling not balanced outcome likes order cancellations and returns (Stylianou & Pantelidou, 2025a). By ensuring transparency and protecting privacy, synthetic data supports reliable diagnostic and predictive modeling without need to real-time control systems (Donker et al., 2025).

2.6.3 The methodological requirements and limitations of synthetic data

Rule-based synthetic data generation ensure distribution realism by probability sampling derived from real history transaction records (Goedhart et al., 2023; Stylianou & Pantelidou, 2025a). Logical rules preserves correct event order also, and ensuring behavioral consistency on the simulated data (Goedhart et al., 2023). This approach require transparency, reproducibility, and strong privacy protection (Donker et al., 2025). modeling rare outcomes like cancellations or returns remain a challenging because of simple sampling may underrepresent them (Günther et al., 2017). Overall, synthetic data supports diagnostic analysis and predictive modeling, presents as a decision-support tool instead a substitute for causal inference or optimization (Donker et al., 2025; Stylianou & Pantelidou, 2025a).

2.7 Predictive Modeling Using Simulated Transactional Data

2.7.1 How effective are simulated datasets in predictive modeling tasks?

The usefulness of synthetic transactional data on e-commerce depends on its ability to training supervised machine-learning models when real data is limited or confidential (Badakhshan et al., 2024). To ensuring stable and generalizable models, the simulated data must matches real distributions closely and maintain correct event order (Donker et al., 2025). Main challenge lie on represent highly not balanced events like cancellations and returns, which requires careful probability design and validation (El Kihal et al., 2025). When it properly constructed, synthetic data can predict order outcomes at placement reliably, and support decision-making without claiming causal inference or optimization (X. Chen, 2025).

2.7.2 What evaluation practices ensure reliability in simulation-based predictive analytics?

To ensuring predictive reliability and diagnostic usefulness within a data-driven framework, supervised machine-learning classification models is validated to establishing generalizability (Donker et al., 2025). Methodological robustness are achieved by stratified K-fold cross-validation, which mitigate overfit by evaluating performance across multiple data partitions while preserving class distributions (Badakhshan et al., 2024). This practice are essential for not balanced e-commerce data, where rare outcomes as cancellations and returns must be detected with high sensitivity (Le et al., 2024a). Accordingly, evaluation rely on metrics suited to distributional skewness, include Precision, Recall, the F1-score, and the Area Under the Curve (AUC) (Donker et al., 2025). Stable performance across validation folds support the use of those models as reliable diagnostic tools to anticipating order outcomes at the point of transaction (Chau et al., 2025).

2.8 Research Gap and Positioning of the Current Study

2.8.1 Research Gap

Most of e-commerce literature have focused on purchase intention, emphasizing theories of technology acceptance, perceived trust, and perceived risk. However, there are a clear lack of studies that focus on actual post-purchase behavior, specifically order cancellations and returns. In other words, the shift from "intention" to "measurable outcome" remains limited, especially when analyzing transaction-level operational data.

Furthermore, the literature has relied heavily on survey data, cognitive measures, and traditional causal models (SEM, regression). In contrast, there is a lack of use of actual operational data or realistic transaction simulations, as well as the application of predictive machine learning models to anticipate cancellations and returns before execution. In addition, there are a lack of integration of Model Explainability tools to understanding the contribution of variables.

The Palestinian market characterized by a high relay on Cash on Delivery (COD), logistical delays and environment instability, weak consumer protecting systems, and restrictions on data sharing. Although, there are a lack of sufficient quantitative predictive studies that analyzing cancellation and return patterns on this context. Most studies focus on stable markets, particularly Asian and European ones. Consequently, there is a lack of analytical models tailored to environments with data constraints and unstable logistical infrastructure.

Accordingly, this study addresses conceptual, methodological, contextual, and practical gaps by modeling cancellation and return behavior by using validated synthetic transaction data and predictive models that could be explained within a business intelligence–driven analytical framework.

2.8.2 Positioning of the Current Study

According to the identified gaps, this study is positioned as a transaction-level analysis of post-purchase behavior on e-commerce, it moving the focus from purchase intention to order outcomes that were observed (completion, cancellation, and return). To addressing data scarcity on Palestinian context, it employs rule-based synthetic data generation that grounded on empirical informed assumptions. Supervised machine-learning models are applied then for predictive and diagnostic purposes in a business intelligence framework. So, the study bridges behavioral theory and operational analytics, and extending data-driven consumer behavior research to emerging, data-constrained markets.

Chapter Three

Research Methodology

3.1 Research Design and Methodological Approach

This study adopts an **applied, exploratory, and diagnostic research design** ground on the field of **business intelligence and data analytics**. The primary objective is analyze historical e-commerce order outcomes—specifically order completion, cancellation and return—through data-driven analytic framework able of supporting operation decision-making. Instead testing predefined causal hypotheses, the study emphasize **post-event behavioral analysis (ex-post analysis)** (Hair Jr et al., 2019) to identifying patterns and factors associated to different orders outcomes. Like design is particularly suitable to complex digital commerce environments where consumers behavior are shaped by multiple operational, temporal and contextual factors (Akter & Fosso Wamba, 2016).

This study adopts an **exploratory** research approach as it addresses a relatively underexplored phenomenon in the Palestinian e-commerce context, particularly in relation to post-purchase behaviors such as order cancellations and returns. The exploratory nature of the study is further justified by the absence of accessible real transactional datasets, which necessitated the development of a theoretically grounded synthetic dataset. This approach allows the study to investigate potential patterns, relationships, and behavioral dynamics that have not been previously examined using transaction-level data in data-constrained environments.

Methodologically, the study is positioning in the diagnostic analytics paradigm, which focus on understanding *why* certain outcomes occurs by examine historical transactional data. Diagnostic analytics have been widely adopted on e-commerce and decision support research for analyze returns, cancellations, and service failures, especially when the objective are improve operational performance rather than establish strict causal inference (Günther et al., 2017). In this context, the study seeks to distinguishing the characteristics of completed, cancelled, and returned orders by analyzing transaction-level attributes, customer-related factors, and time-dependent conditions.

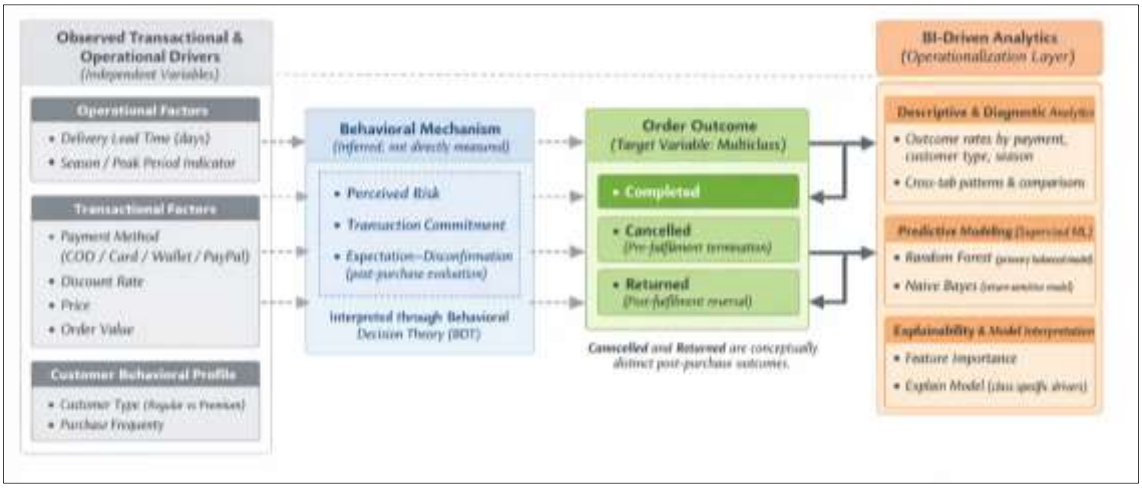
Because of the unavailability of real transactional datasets from Palestinian e-commerce platforms, and considering the sensitivity and confidentiality of data like that, the study relies on a synthetic data–driven methodology. The using of synthetic data on information systems and business analytics research have been increasingly recognized as valid methodological alternative when access to proprietary or sensitive data are restricted, provided that the data generation processes is transparent, rule-based, and grounded of empirical evidence (Drechsler, 2011). Therefore, the research design integrate empirical distributions extracted from external reference datasets to domain-informed operational rules reflecting the Palestinian e-commerce context.

Overall, the adopting methodological approach allow the study to balancing analytical stringent and practical relevance. Through combine exploratory analysis with structured simulation framework, the research contribute replicable and explainable analytical model that could be utilized by practitioners and researchers to better understanding order cancellations and returns in emerging e-commerce markets.

Figure 1 illustrate the research model adopt on this study. The model conceptualize online order outcomes as observable post-purchase behaviors influenced by transactional, operational, and customer-related factors. These relationships is operationalized through a business intelligence–driven analytical framework that integrate descriptive diagnostics and supervised predictive modeling for support data-driven decision making.

Figure 1

Research Model



3.2 Data Sources and Reference Datasets

The data utilized in this study is derived from two complementary sources:

1. Publicly available references datasets got from Kaggle.
2. Domain-informed practical knowledge gleaned from expert elicitation through individual call interviews of online retailers in Palestine.

This dual-source approach were adopted to ensuring both empirical grounding and contextual relevance, particularly on setting where access to proprietary transactional data is restricted so badly.

The primary reference datasets was obtained from Kaggle, open data platform widely used on academic researches for benchmarking, methodological validation and exploratory analytics. The dataset were originally collected by the Pakistani researcher Zeeshan-ul-Hassan via online web scraping techniques, as part of research study. The data was collected from various real e-commerce retailers operating in Pakistan, reflecting actual consumer transaction behavior. And where the Pakistani market is somehow similar to the Palestinian one.

In this study, Kaggle datasets was not used directly to derive final analytical result. Instead, they served as reference distributions to informing the structure of synthetic data, including product category composition, return reason typologies and temporal orders patterns. This practice align with generated guidelines to synthetic data generation, where real datasets is employed to preserving statistical realism while avoiding privacy and confidentiality risks (Drechsler, 2011).

In addition to Kaggle reference data, several operational facts—like payment method prevalence, approximate return and cancellation rates and customer behavior during promotional periods—were obtained by informal verbal communication with e-commerce retailers operating in the Palestinian market. Those inputs were collected as aggregated, non-identifiable, and approximate insights, with explicit refusal by participants to disclosing company names or any proprietary matters. From a methodological standpoint, this shape of knowledge acquisition correspond to expert elicitation, recognized technique on applied analytics and decision support research when hard data is not available or not accessible (Garthwaite et al., 2005).

Importantly, the verbally elicited information was not treated as statistically exact measurement, but rather as contextual constraint and plausibility bounds guides the simulation rules (e.g., relative dominance of cash-on-delivery payment or absence of order cancellations with loyal customers). Similar approaches was documented in operations research and information system studies that dealing with data-scarce environments (Garthwaite et al., 2005).

Generally, the mix of Kaggle datasets and expert-informed contextual rules ensure that the generated synthetic dataset reflects realistic behavioral patterns with remaining ethically sound, replicable, and independent of sensitive commercial data.

3.3 Synthetic Data Simulation Approach

The study adopts **synthetic data** simulation approach to construct realistic and analytically valid dataset represent customer order outcomes on e-commerce environments, namely order completion, cancellation, and return. Where synthetic data simulation enable researchers to generating large-scale datasets that preserve the statistical properties, behavioral pattern, and structural relationship observed on real-world systems. Accordingly, synthetic datasets may support robust predictive modeling and decision-making task, provided that the simulation process are grounded on empirical evidence and domain-specific assumptions (Drechsler, 2011).

In this study, the simulation process is guided by hybrid design that combine:

1. **External benchmark datasets** obtained from publicly available e-commerce repositories (real datasets transactions).
2. **Contextual business rule and empirical ratios** reflect operational characteristics of Palestinian e-commerce markets, as reported by aggregated practitioner insights.

The simulation framework follow rule-based probabilistic modeling strategy, where key variables —like payment methods, delivery time, discount availability, customers type, and order value—is generated based on predefined probability distributions and condition constraints. Those constraints are explicitly designed to reflecting realistic operational logic; for example, order cancellations occur exclusively before shipment, and return status are conditionally dependent on delivery outcome and documented return reasons.

Unlike totally random data generation technique, the adopted approach ensure that causal plausibility and temporal coherence are maintained through observation. This design choice enhance the external validity of the experiment of later predictive modeling, specifically when applying supervised machine learning algorithms to classifying order outcomes.

So, the using of synthetic data in this study isn't methodological limitation, but rather a deliberate and theoretically supported strategy which enable controlled experimentation, scalability, and reproducibility, with maintaining alignment with real-world e-commerce dynamics.

3.4 Data Generation and Simulation Process

3.4.1 Data Schema and Variable Definition

All variables included on the dataset was selected based on its theoretical relevance to post-purchase customers behavior and practical observability on real-world e-commerce systems.

The data schema is designed to supporting multi-class classification task, the order status variable represents the dependent outcome and the remaining variables is independent or descriptive features.

A synthetic historical e-commerce dataset was generated using rule-based simulation approach informed by real market practices. Several key variable distributions—like payment methods, customer gender, and order outcomes—were fixed based of practitioner insights from Palestinian market. Product categories and return reason was modeled by using empirical distributions derived from external reference datasets. To ensuring realism and internal consistency, temporal and logical constraint were applied between order status, delivery dates, discounts, and return reasons. This approach enables robust diagnostic and analytical investigation of order completion, cancellation, and return behavior without rely on proprietary transactional data.

Additionally, seasonal indicator variable (Season) was derived from order date to capture detailed temporal patterns in customer behavior. Orders were classified into four seasons (Spring, Summer, Autumn, Winter) based on their order date. This derived variable was included as independent feature to account for potential seasonal effecting on e-commerce order outcomes. See Table 1, Appendix B.

3.4.2 Simulation Assumptions

The synthetic dataset used on this study is generated based on a set of **explicit simulation assumptions** designed to ensuring statistical realism and behavioral consistency along with real-world e-commerce operation. Clearly defining simulation assumptions are fundamental requirement on synthetic data research, as it enhance transparency, reproducibility, and methodological validity (Liang & Hu, 2024). Table 2 shows the general synthetic data generation rules.

Table 2

Synthetic Data Generation Rules

Domain	Rule	Implementation in Data
Order Status (Base Rates)	Returned 30%, Cancelled 8%, Completed 62%	Initial distribution of target variable
Order Cancellation	All cancelled orders occur before shipping	If order_status = Cancelled → delivered_date = NULL and return_reason = NULL
Order Returns	Return reason exists only for returned orders	If order_status = Returned → return_reason filled, otherwise NULL
Payment Method	Four methods with fixed shares	COD 75%, Card 15%, Wallet 6%, PayPal 4%
Customer Gender	Fixed gender distribution	Female 69%, Male 31%
Product Category	Based on external dataset	Categories sampled using empirical distribution
Return Reasons	Based on external dataset (conditional)	Reasons sampled only within returned orders
Slow Delivery Constraint	"Slow delivery" appears only after Black Friday	Probability = 0 during BF, allowed post-BF
Delivery Time (Normal Period)	3–5 days	Orders outside BF with status Completed/Returned
Delivery Time (Black Friday)	Up to 14 days	Orders during BF with status Completed/Returned
Price Range	10–500 ILS	Furniture excluded or handled separately
Quantity	Mostly single-item orders	1 item = 90%, 2–3 items = 10%
Discount Values	Limited to three values	discount_rate ∈ {0, 0.05, 0.10}
5% Discount Rule	Loyal customers or larger quantities	If customer_type = Premium or quantity > 1
10% Discount Rule	Black Friday promotion	If order_date within BF
Discount Effect	Discount reduces cancellation/ return risk	If discount_rate > 0 → (Returned + Cancelled) < 5%
Loyal Customers – Cancellation	No cancellations allowed	If customer_type = Premium → Cancelled = 0%
Loyal Customers – Returns	Very rare and only for strong reasons	Mainly Defective, Missing/Wrong item, Not as described
Customer Segmentation	Quantile-based classification	Premium = top 25% (Q75) by order count

The first assumption concern nature of the data itself. All generated record are treated as completed historical transaction, meaning that every observation reflect a order that have already entered the operational system and reached one of three mutually exclusive outcomes: completed, cancelled, or returned. Treating synthetic data as ex-post transactional record align with best practices on business process simulation and avoid ambiguity in outcome interpretation (Badakhshan et al., 2024).

A second core assumption relates to temporal structure of orders. Order dates is uniformly distributed between January 1, 2023 and December 31, 2025, reflecting continuous operational environment instead short-term experimental snapshot. Modeling time as continuous process is essential in e-commerce analytics, as seasonality and operational load significantly influence customer behavior and fulfillment performance (Stylianou & Pantelidou, 2025b).

The simulation further assume that order cancellation events occur exclusively before shipment or delivery, and so, cancelled orders do not have associated delivery date. This assumption reflect standard operational policies on e-commerce logistics and is widely supported in order fulfillment literature (Chopra & Meindl, 2016).

In contrast, returned orders is assumed to occur only after successful delivery, and each return is associated with documented return reason. This distinction between cancellation and return is critical for maintain causal and temporal validity in post-purchase behavior analysis (Marchand & Marx, 2020).

Another key assumption concern delivery time. According to e-commerce sellers; for regular order, delivery duration is assumed to range between 3 and 5 days, while orders placed during the Black Friday period maybe experience extended delivery times up to 14 days due to increased demand and logistical congestion. Integrating delivery delays during peak seasons reflect empirically observed patterns on e-commerce supply chains (Borodin et al., 2016).

Regarding pricing behavior, product prices is constrained to realistic range between 10 and 500 ILS. Defining realistic value ranges is common requirement on synthetic economic data generation to prevents artificial outliers (Drechsler, 2011).

Order quantity is assumed to be mainly individual-based, with approximately 90% of orders containing one unit, while multi-unit orders occur on lower frequencies. This assumption reflect documented purchasing patterns on online retail, where single-item orders dominate consumer transactions (Huang et al., 2015).

Discount application follow rule-based assumption: discount are granted to loyal (premium) customers or applied during promotional periods like Black Friday. also, when discount is present, the probability of cancellation or return is assumed to drop below 5%. This assumption is supported by empirical studies show that promotional incentive reduce post-purchase regret and order abandonment behavior (Mofokeng, 2023).

Customer segmentation on this study is performed by using distribution-based approach, where customers who purchasing frequency fall above the 75th percentile (Q75) are classified as premium customers, and the remaining customers are categorized as regular. The use of the Q75 threshold provide a objective, data-driven criterion that avoid arbitrary cut-off points and allows customer status to emerge naturally from observed behavioral patterns (Giannuzzi et al., 2023).

Finally, the simulation assume the existence of customer segmentation, distinguishing between regular and premium customers. Premium customers are assumed not to cancel orders, while returns among this group are rare and occurs only under strong justifiable reasons. Modeling customer heterogeneity is essential in predictive analytics, as customer loyalty significantly moderates post-purchase behavior. The summary of simulation assumptions applied in this study are summarized in appendix A.

3.5 Synthetic Data Generation Process

This section describes the procedural steps followed to generate the synthetic e-commerce dataset used in this study by using Python programing language.

Step 0: preparing the environment and importing external data to extract the distribution

a. Preparing environment and importing external data:

```
import numpy as np
import pandas as pd
from datetime import datetime, timedelta

np.random.seed(42)  # reproducibility

external_path = r"C:/Users/USER/Desktop/3 الرسالة/data external/Kaggle_Ecommerce Data.csv"
ext = pd.read_csv(external_path)

ext.head(), ext.columns
```

b. Specify columns name (Category and Return reason) and their distributions:

```
[c for c in ext.columns if "cat" in c.lower() or "reason" in c.lower() or "return" in c.lower()]

cat_col = "category"
reason_col = "return_reason"

category_probs = (
    ext[cat_col]
    .dropna()
    .astype(str)
    .value_counts(normalize=True)
)

category_probs

ext[reason_col].dropna().astype(str).value_counts(normalize=True).head(20)
```

And then, keep only the five common reasons (as adopted in assumptions):

```
allowed_reasons = [
    "Defective",
    "Not as described",
    "No longer needed",
    "Missing/Wrong item",
    "Slow delivery"
]

reason_probs_raw = (
    ext[reason_col]
    .dropna()
    .astype(str)
    .value_counts(normalize=True)
)

# Keep only allowed reasons; renormalize
reason_probs = reason_probs_raw[reason_probs_raw.index.isin(allowed_reasons)]
reason_probs = reason_probs / reason_probs.sum()

reason_probs
```

```
return_reason
Not as described      0.257488
No longer needed      0.252759
Defective             0.244351
Missing/Wrong item    0.230688
Slow delivery         0.014714
Name: proportion, dtype: float64
```

Step 1: Sitting up the simulation parameters (establish the facts)

```
N = 30000  # data size
payment_methods = ["COD", "Card", "Wallet", "PayPal"]
payment_probs = [0.75, 0.15, 0.06, 0.04]

genders = ["Female", "Male"]
gender_probs = [0.69, 0.31]

# Order status base (before business-rule adjustments)
status_labels = ["Returned", "Cancelled", "Completed"]
status_probs = [0.30, 0.08, 0.62]

# Quantity distribution
qty_values = [1, 2, 3]
qty_probs  = [0.90, 0.07, 0.03]

# Price range
PRICE_MIN, PRICE_MAX = 10, 500

# Black Friday window
BF_START = pd.Timestamp("2025-11-20")
BF_END   = pd.Timestamp("2025-11-30")
```

Step 2: Generating columns for identify, time and key characteristics

```
# IDs
order_id = np.arange(1, N+1)

# to make repeats, we generate customer_id and product_id with limited pools
n_customers = max(500, N // 10)
n_products  = max(300, N // 20)

customer_id = np.random.randint(1, n_customers+1, size=N)
product_id  = np.random.randint(1, n_products+1, size=N)

# Order dates
start_date = pd.Timestamp("2023-01-01")
end_date   = pd.Timestamp("2025-12-31")
date_range_days = (end_date - start_date).days

order_date = start_date + pd.to_timedelta(np.random.randint(0, date_range_days+1, size=N), unit="D")

# Category (from external distribution)
categories = category_probs.index.tolist()
cat_probs  = category_probs.values

category = np.random.choice(categories, size=N, p=cat_probs)

payment_method = np.random.choice(payment_methods, size=N, p=payment_probs)
customer_gender = np.random.choice(genders, size=N, p=gender_probs)

quantity = np.random.choice(qty_values, size=N, p=qty_probs)

# Price:
price = np.random.uniform(PRICE_MIN, PRICE_MAX, size=N).round(2)

df = pd.DataFrame({
    "order_id": order_id,
    "product_id": product_id,
    "customer_id": customer_id,
    "category": category,
    "order_date": order_date,
    "quantity": quantity,
    "price": price,
    "payment_method": payment_method,
    "customer_gender": customer_gender
})

df.head()
```

Step 3: establish customer type Premium/Regular (Quantile Q75)

```
# Premium/Regular (Quantile Q75)
orders_count = df.groupby("customer_id")["order_id"].transform("count")
q75 = orders_count.quantile(0.75)

df["customer_type"] = np.where(orders_count >= q75, "Premium", "Regular")
df["customer_type"].value_counts(normalize=True)
```

Step 4: establish the discount

```
is_bf = (df["order_date"] >= BF_START) & (df["order_date"] <= BF_END)

df["discount_rate"] = 0.0

# Black Friday discount (10%) - apply to most BF orders (e.g., 80%)
bf_mask = is_bf & (np.random.rand(N) < 0.80)
df.loc[bf_mask, "discount_rate"] = 0.10

# 5% discount for Premium customers or larger quantities (outside BF, or where BF discount not applied)
eligible_5 = (df["discount_rate"] == 0) & ((df["customer_type"] == "Premium") | (df["quantity"] > 1))
df.loc[eligible_5 & (np.random.rand(N) < 0.70), "discount_rate"] = 0.05  # 70% of eligible get it
```

Assessment discount rate:

```
df["discount_rate"].value_counts(normalize=True)
```

```
discount_rate
0.00    0.735267
0.05    0.257000
0.10    0.007733
Name: proportion, dtype: float64
```

Step 5: establish the order status according to the rules

```
df["order_status"] = np.random.choice(status_labels, size=N, p=status_probs)

# Rule: Premium customers -> no cancellations
Premium_mask = df["customer_type"] == "Premium"
df.loc[Premium_mask & (df["order_status"] == "Cancelled"), "order_status"] = "Completed"

# Rule: Discount reduces (Returned + Cancelled) to < 5%
disc_mask = df["discount_rate"] > 0
# For discounted orders, force status mostly to Completed
# We'll re-sample their statuses with: Returned 3%, Cancelled 1%, Completed 96%  (sum < 5% for bad outcomes)
disc_status = np.random.choice(
    ["Returned", "Cancelled", "Completed"],
    size=disc_mask.sum(),
    p=[0.03, 0.01, 0.96]
)
df.loc[disc_mask, "order_status"] = disc_status

# Rule: Premium returns are very rare (e.g., 2%) and never cancelled already ensured
# If Premium & returned, keep only a small fraction as returned, rest completed
Premium_return_mask = Premium_mask & (df["order_status"] == "Returned")
keep_return = np.random.rand(Premium_return_mask.sum()) < 0.02
df.loc[Premium_return_mask, "order_status"] = np.where(keep_return, "Returned", "Completed")
```

Assessment order status:

```
df["order_status"].value_counts(normalize=True)
```

```
order_status
Completed    0.749133
Returned     0.195867
Cancelled    0.055000
Name: proportion, dtype: float64
```

Step 6: generate delivery time and delivery date

a. Determining Black Friedy period for each year:

```
def is_black_friday(date):
    return (
        (date.month == 11) and (date.day >= 20) and (date.day <= 30)
    )

df["is_bf"] = df["order_date"].apply(is_black_friday)
```

b. Generate delivery time:

```
df["delivery_lead_time_days"] = np.nan

mask_delivered = df["order_status"].isin(["Completed", "Returned"])

# Outside Black Friday → 3-5 days
mask_normal = mask_delivered & (~df["is_bf"])
df.loc[mask_normal, "delivery_lead_time_days"] = np.random.randint(
    2, 6, size=mask_normal.sum()
)

# During Black Friday → 3-14 days
mask_bf = mask_delivered & (df["is_bf"])
df.loc[mask_bf, "delivery_lead_time_days"] = np.random.randint(
    3, 15, size=mask_bf.sum()
)
```

c. Calculate delivery date:

```
df["delivered_date"] = pd.NaT

df.loc[mask_delivered, "delivered_date"] = (
    df.loc[mask_delivered, "order_date"] +
    pd.to_timedelta(df.loc[mask_delivered, "delivery_lead_time_days"], unit="D")
)
```

Step 7: Generating return reason

a. Preparing column and identifying reasons list:

```
df["return_reason"] = None
# All allowed reasons
all_reasons = [
    "Defective",
    "Not as described",
    "No longer needed",
    "Missing/Wrong item",
    "Slow delivery"
]

# Strong reasons (for premium customers)
strong_reasons = [
    "Defective",
    "Not as described",
    "Missing/Wrong item"
]
```

b. Reasons distribution from external data:

```
reason_probs
```

```
return_reason
Not as described      0.257488
No longer needed      0.252759
Defective             0.244351
Missing/Wrong item    0.230688
Slow delivery         0.014714
Name: proportion, dtype: float64
```

c. Applying rules:

```
# Mask for returned orders
returned_mask = df["order_status"] == "Returned"

# Returned orders DURING Black Friday → no "Slow delivery"
mask_return_bf = returned_mask & df["is_bf"]

# Returned orders AFTER Black Friday
mask_return_postbf = returned_mask & (~df["is_bf"])

# Premium customers
mask_Premium = df["customer_type"] == "Premium"
```

d. Returns during Black Friedy:

```
allowed_bf_reasons = [r for r in all_reasons if r != "Slow delivery"]

bf_reason_probs = reason_probs.loc[reason_probs.index.isin(allowed_bf_reasons)]
bf_reason_probs = bf_reason_probs / bf_reason_probs.sum()

df.loc[mask_return_bf, "return_reason"] = np.random.choice(
    bf_reason_probs.index,
    size=mask_return_bf.sum(),
    p=bf_reason_probs.values
)
```

e. Returns after Black Friedy (regular customer):

```
mask_regular_postbf = mask_return_postbf & (~mask_frequent)

df.loc[mask_regular_postbf, "return_reason"] = np.random.choice(
    reason_probs.index,
    size=mask_regular_postbf.sum(),
    p=reason_probs.values
)
```

f. Returns after Black Friedy (premium customer):

```
# Strong reasons only
strong_reason_probs = reason_probs.loc[reason_probs.index.isin(strong_reasons)]
strong_reason_probs = strong_reason_probs / strong_reason_probs.sum()

mask_Premuim_postbf = mask_return_postbf & mask_Premium

df.loc[mask_Premium_postbf, "return_reason"] = np.random.choice(
    strong_reason_probs.index,
    size=mask_Premium_postbf.sum(),
    p=strong_reason_probs.values
)
```

Assessment:

```
df.loc[df["order_status"] != "Returned", "return_reason"].isna().all()
```

```
np.True_
```

```
df.loc[df["is_bf"] & (df["return_reason"] == "Slow delivery")].shape[0]
```

```
0
```

```
df.loc[
    (df["customer_type"] == "Premium") & (df["order_status"] == "Returned"),
    "return_reason"
].value_counts()
```

```
return_reason
Defective             12
Not as described       8
Missing/Wrong item     6
Name: count, dtype: int64
```

Step 8: calculate order value

```
df["order_value"] = (
    df["price"] * df["quantity"] * (1 - df["discount_rate"])
).round(2)
```

Step 9: cleaning and columns arrangement

```
final_columns = [
    "order_id", "product_id", "customer_id",
    "customer_type", "customer_gender",
    "category",
    "order_date", "delivered_date", "delivery_lead_time_days",
    "order_status", "return_reason",
    "quantity", "price", "discount_rate", "order_value",
    "payment_method"
]

df = df[final_columns]
df.head()
```

Step 10: save data into csv file

```
df.to_csv("synthetic_ecommerce_orders_2023_2025.csv", index=False)
# Export  to csv
output_pathh = r"C:/Users/USER/Desktop/df.csv"

df.to_csv(output_pathh, index=True)

print("Excel file saved successfully at:", output_pathh)
```

```
Excel file saved successfully at: C:/Users/USER/Desktop/df.csv
```

3.6 Data Validation and Consistency Checks

To ensuring the methodological robustness and internal validity of generated synthetic dataset, comprehensive set of data validation and consistency checks were conducted following the data generation process.

On the distributional level, the final dataset of 30,000 orders were examined to verifying alignment with controlled behavioral outcomes that imposed during simulation. After apply business rules related on discounts, customer loyalty, and seasonal effects, the observed outcome distribution consisted of approximately 74.9% completed orders, 19.6% returned orders, and 5.5% cancelled orders. Although the initial target ratios was set at 62% completed, 30% returned, and 8% cancelled, the deviation observed in the final dataset are methodologically justified.

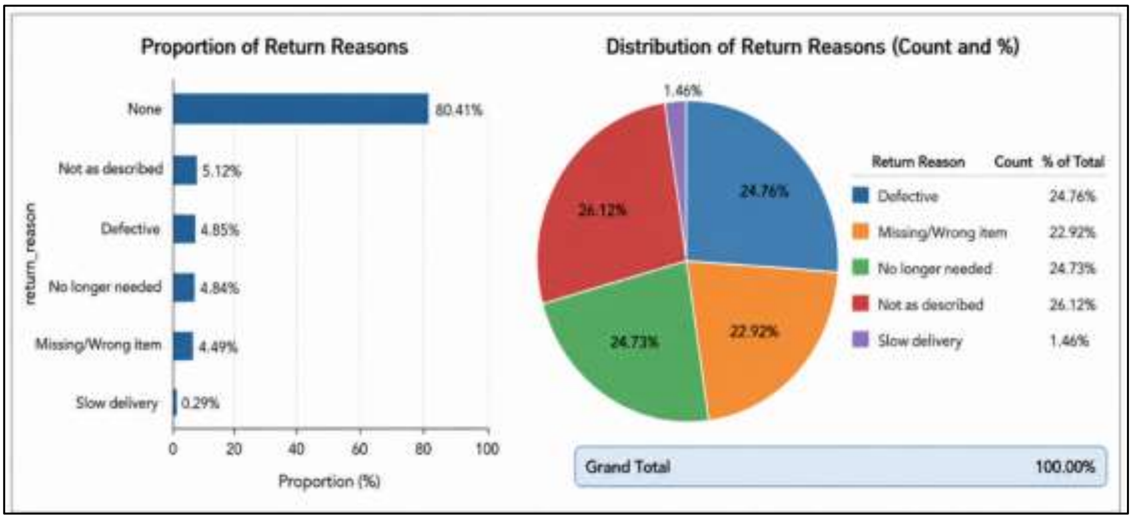
Prior research emphasize that rule-based constraint—like reduced return and cancellation probability under promotional conditions—are expected to alter marginal distributions and should be interpreted as reflection of realistic operational dynamics instead of simulation bias (Z. Chen et al., 2023; El Kihal et al., 2025).

Logical consistency checks were then applied on the transaction level to eliminate contradictory or implausible record. All cancelled order were verified to have no delivery date and no return reason, ensure temporal and semantic coherence between order status and fulfillment variables. On the other hand, all completed and returned order were associated with valid delivery dates, with delivery lead times strictly bounded by the predefined ranges of 3–5 days during normal period and up to 14 days during the Black Friday period.

Additional validation has focused on the return reason variable, which was populated exclusively for returned orders. Empirical checks have confirmed that approximately 80% of all records contained no return reason, consistent to the final proportion of non-returned orders. Between returned orders, most frequent reasons were: Not as described, Defective, No longer needed, and Missing/Wrong item, and Slow delivery represent less than 0.1% of total records. This low incidence consistent with the imposed temporal restriction allow these reasons only in post–Black Friday periods, thus reinforcing the seasonal logic embedded in the simulation. See figure 2.

Figure 2

Return Reasons Distribution



Finally, customer segmentation consistency were assessed by validate the quantile-based classification of customer in regular and premium segments. Using the 75th percentile threshold of order frequency, the resulting distribution have yielded approximately 68.6% regular customers and 31.4% premium customers. The absence on cancelled orders among frequent customers and the rarity of returns in this segment further confirms the correct enforcement of loyalty-based behavioral rules. See figure 3.

Figure 3

Customers Type Distribution

```
customer_type
Regular    0.686033
Premium    0.313967
Name: proportion, dtype: float64
```

Generally, those validation procedures confirms that the synthetic dataset satisfy key criteria of internal consistency, logical coherence, and analytical realism. Instead of aiming for exact replication of real-world statistics, the dataset is validated as fit-for-purpose to exploratory and diagnostic analysis of order outcomes, that align with established methodological guidance for synthetic data use on business intelligence research (Khamis Mwero Manero et al., 2018).

Table 3 summarizes the validation procedures applied to the synthetic dataset, confirming that all structural, logical, temporal, and behavioral constraints was successfully enforced and that generated data are internally consistent and analytically reliable.

Table 3

Summary of Validation Procedures

Validation Aspect	Rule / Expected Condition	Observed Outcome (Python Results)	Validation Status
Dataset size	Synthetic dataset size	30,000 orders generated	✓ Valid
Order status distribution	Completed, Returned, Cancelled after rule application	Completed ≈ 74.9%, Returned ≈ 19.6%, Cancelled ≈ 5.5%	✓ Valid
Cancelled orders – delivery date	Cancelled orders must not have delivery dates	All cancelled orders have delivered_date = NULL	✓ Valid
Cancelled orders – return reason	Cancelled orders must not have return reasons	All cancelled orders have return_reason = NULL	✓ Valid
Completed/Returned orders – delivery date	Must have valid delivery dates	100% of completed and returned orders have delivery dates	✓ Valid
Delivery lead time (normal period)	3–5 days outside Black Friday	Observed lead times strictly within range	✓ Valid
Delivery lead time (Black Friday)	Up to 14 days during Black Friday	Observed lead times up to 14 days only	✓ Valid
Return reason population	Return reasons only for returned orders	≈ 80% of records have no return reason	✓ Valid
Return reason distribution	Empirically plausible dominant reasons	Most frequent: Not as described, Defective, Missing/Wrong item	✓ Valid
Slow delivery constraint	Allowed only after Black Friday	< 0.1% of total records, none during BF	✓ Valid
Customer segmentation	Quantile-based (Q75) segmentation	Regular ≈ 68.6%, premium ≈ 31.4%	✓ Valid
Frequent customers – cancellation	No cancellations allowed	0 cancelled orders among frequent customers	✓ Valid
Frequent customers – returns	Rare returns with strong reasons only	Returns observed only for strong reasons	✓ Valid
Discount effect	Discount reduces return/cancellation probability	Discounted orders show < 5% Returned + Cancelled	✓ Valid

3.7 Predictive Modeling Using Orange

This section presents the predictive modeling stage implement using Orange data mining platform, aiming to develop and evaluate classification models capable of predicting order return behavior on e-commerce context. The Orange Data Mining tool was selected due to its strong suitability for exploratory and diagnostic analytics within a business intelligence context. It offers an interactive visual programming environment that enables efficient development, testing, and comparison of machine learning models, along with integrated tools for data preprocessing, visualization, and performance evaluation. In addition, Orange is continuously updated to keep pace with advancements in data science and machine learning, ensuring the use of modern and reliable analytical techniques. It is also widely recognized and adopted in academic research and education, which further supports its credibility and appropriateness for this study.

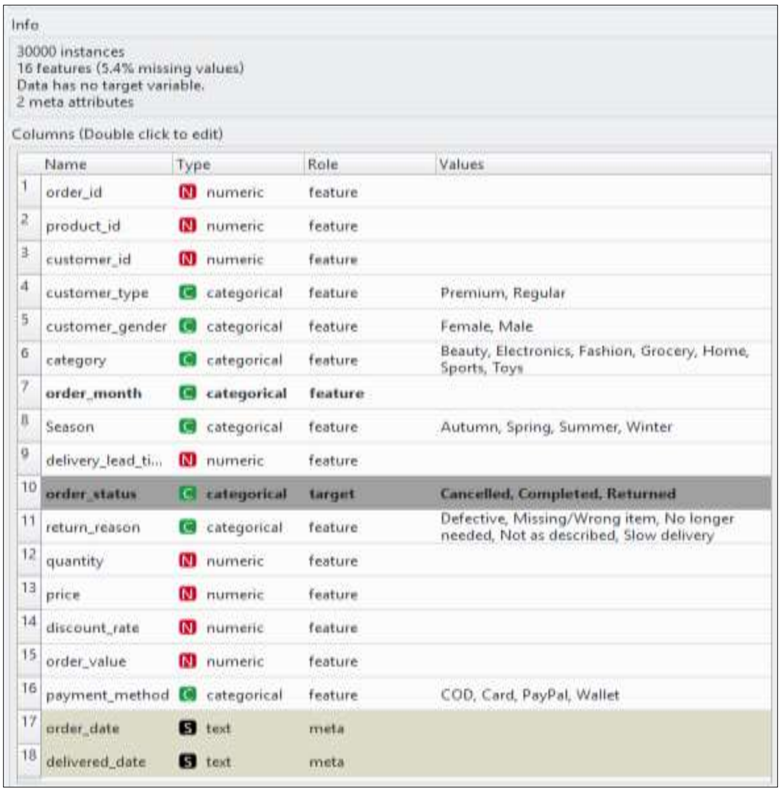
Predictive modeling represent core component of business intelligence and data analytics research, as it enable the transformation of historical transactional data to actionable insights that support anticipatory decision-making rather than post-hoc interpretation (Le et al., 2024b). In the context of e-commerce analytics, machine learning–based classification model has been widely adopted to predicting binary outcomes like purchase completion, churn, and product returns, because of their ability to capture complex relationships between customer attributes, transactional features, and behavioral outcomes. Accordingly, this study adopts supervised learning framework to model the likelihood of order returns or completed based on preprocessed transactional and customer-related variables, using Orange as integrated visual analytics environment which supports transparent workflow design, model comparison, and reproducibility of analytical procedures.

3.7.1 Data Source Loading and Initial Configuration

The predictive modeling workflow commenced with the ingestion of the simulated transactional dataset using Orange's File widget. This component was employed to load the dataset in comma-separated values (CSV) format and to establish the initial data schema prior to any preprocessing or modeling activities. Data loading represents critical primary step on predictive analytics workflows, as it enables verification of dataset structure, variable types, and roles assignments before applying further transformations. See figure 4.

Figure 4

Data Loading and Initial Configuration



Info

30000 instances
16 features (5.4% missing values)
Data has no target variable.
2 meta attributes

Columns (Double click to edit)

	Name	Type	Role	Values
1	order_id	numeric	feature	
2	product_id	numeric	feature	
3	customer_id	numeric	feature	
4	customer_type	categorical	feature	Premium, Regular
5	customer_gender	categorical	feature	Female, Male
6	category	categorical	feature	Beauty, Electronics, Fashion, Grocery, Home, Sports, Toys
7	**order_month**	**categorical**	**feature**	
8	Season	categorical	feature	Autumn, Spring, Summer, Winter
9	delivery_lead_ti...	numeric	feature	
10	**order_status**	**categorical**	**target**	**Cancelled, Completed, Returned**
11	return_reason	categorical	feature	Defective, Missing/Wrong item, No longer needed, Not as described, Slow delivery
12	quantity	numeric	feature	
13	price	numeric	feature	
14	discount_rate	numeric	feature	
15	order_value	numeric	feature	
16	payment_method	categorical	feature	COD, Card, PayPal, Wallet
17	order_date	text	meta	
18	delivered_date	text	meta	

At loading, the dataset comprised 30,000 instances and mix of numerical and categorical attributes represent transactional, customer-related, and order-level information. within this stage, all variable were inspected and assigned explicit roles, distinguish between predictor features, the target variable, and meta-attributes. The target variable was defined as order status, formulated as a multiclass categorical outcome (Cancelled, Completed, Returned), and identifier and date-related variables (e.g., order and delivery dates) was designated as meta-attributes to excluding them from the learning process. exact role assignment at this stage are essential to preventing unintended feature usage and to ensuring methodological clarity on supervised learning tasks (Donker et al., 2025).

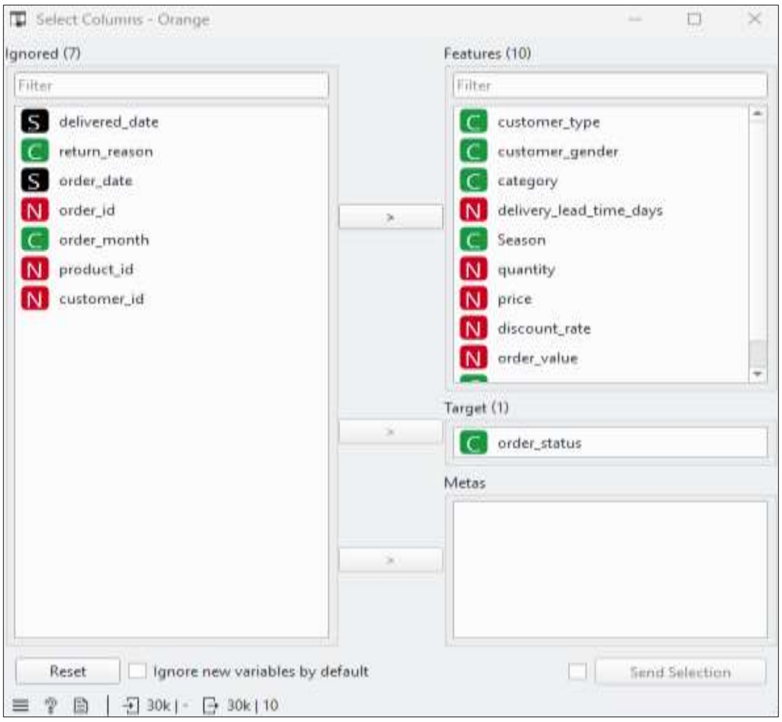
3.7.2 Feature Selection and Target Specification

Following data ingestion, feature selection step was conducted by using Orange's Select Columns widget to explicitly define predictor variables, target variable and excluded attributes. Feature selection constitute critical component of predictive modelling, as the inclusion of irrelevant, redundant, or target-dependent variables can adversely affect model performance and compromise generalization ability.

Identifier field (e.g., order ID, product ID, customer ID), temporal attributes (e.g., order date, delivered date), and outcome dependent variables (e.g., return reason) were purposely excluded from modelling process. Excluding these variables is standard practice to prevent information leakage, reduce noise and avoid predictive performance that artificially inflated. See figure 5.

Figure 5

Feature Selection and Target Specification



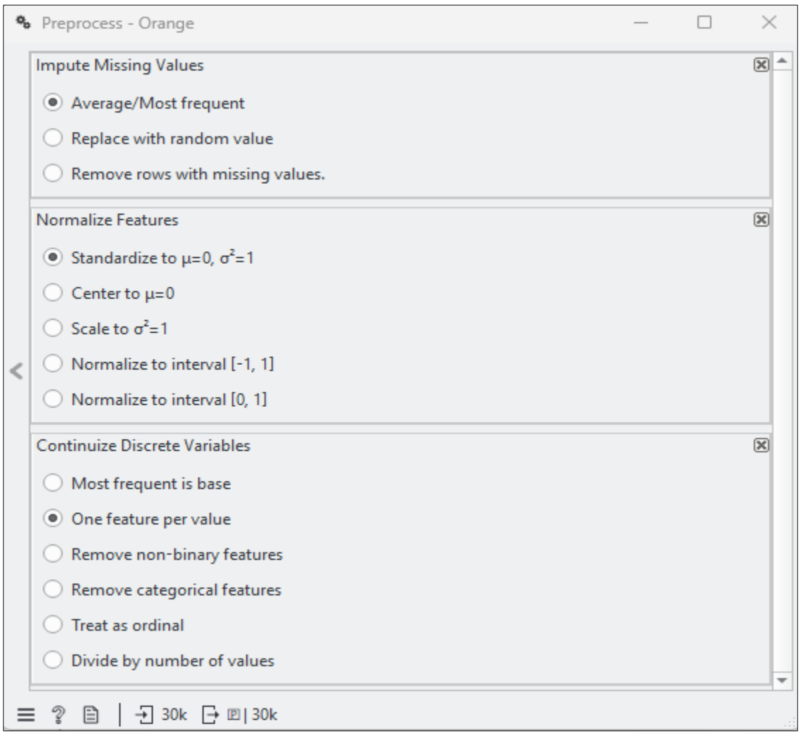
Importantly, feature selection process was conducted repetitive, where multiple configurations was tested by selectively excluding non-informative or redundant variables to improving model stability and predictive accuracy. Iterative feature refinement aligns with best practices on applied machine learning research, particularly on exploratory predictive modeling, where model performance is sensitive to feature composition (Kuhn & Johnson, 2013) . The final feature set were fixed after achieving balanced trade-off between model performance, interpretability, and methodological validity.

3.7.3 Data Preprocessing Configuration

The preprocessing stage were implemented by using Orange's Preprocess widget to preparing selected features for multiclass supervised classification. Preprocessing is critical step in predictive modeling, as it's addresses data incompleteness, scale heterogeneity, and categorical representation on an unified and reproducible manner (Kuhn & Johnson, 2013). The following configurations was applied see figure 6:

Figure 6

Data Preprocessing



Imputation of Missing Values

Missing values were handled using the average/most frequent imputation strategy. In the analyzed dataset, missingness was confined to the delivery lead time attribute and occurred exclusively for cancelled orders, where actual delivery didn't take place. Accordingly, imputing missing delivery lead times with average value represent logical approximation, as its reflect the estimated delivery duration instead an observed post-outcome measure. Mean imputation on case like that is considered appropriate when missingness is structurally linked to the process under study and doesn't introduce target leakage (Kuhn & Johnson, 2013).

Feature Normalization

Numerical variables was standardized to zero mean and unit variance ($\mu = 0$, $\sigma^2 = 1$). Standardization reduces scale-related bias and ensure compatibility across classifiers that is sensitive to feature magnitude, like margin-based and distance-based models.

Continuization of Categorical Variable

Categorical features were transformed by using a one-feature-per-value encoding scheme, enable its use on algorithms that require numerical input without imposing artificial ordinal relationship. This approach preserves categorical information and maintaining model flexibility on multiclass classification task.

All preprocessing operations were applied through a single shared preprocessing component and subsequently fed into all classification models, ensuring methodological consistency and fair performance comparison across learners.

3.7.4 Selected Classification Algorithms

To ensure robust and unbiased predictive modeling, the study employed multiple classification algorithm with diverse theoretical foundation and learning assumptions. Using heterogeneous set of classifiers are a common practice on applied machine learning research, as its enable comparative evaluation and reduces risk of model-dependent bias, particularly on multiclass classification problems. All models were trained in identically preprocessed data to ensuring methodological consistency and fair comparison. Unless otherwise stated, default parameter setting provided by Orange platform was adopted to establish baseline model performances and enhance reproducibility (Kuhn & Johnson, 2013).

Logistic Regression

Logistic Regression was employed as baseline linear classifier due to its interpretability and widespread use on modeling categorical outcomes. Despite its linear decision boundary, logistic regression provides valuable reference point to assessing the added value of other complex non-linear models on multiclass classification tasks (Hastie & Pregibon, 1992).

Naïve Bayes

The Naïve Bayes classifier was included to its probabilistic foundation and computational efficiency. Its strong independence assumption, even simplistic, often yields competitive performance on high-dimensional categorical data and provides a contrasting modeling perspective relative to discriminative classifiers (Kuhn & Johnson, 2013).

Support Vector Machine (SVM)

Support Vector Machines was applied because of its ability to construct an optimal decision boundary in high-dimensional feature spaces. SVMs are particularly effective at handling complex class separation and have been widely adopted on e-commerce and customer behavior prediction studies (Hastie & Pregibon, 1992).

Decision Tree

Decision Tree classifier was incorporated to provide a rule-based, interpretable modeling approach. Decision trees are well-suited for capturing non-linear relationships and interaction between features and offering transparent decision logic, which is valuable in business intelligence contexts (Hastie & Pregibon, 1992).

Random Forest

Random Forest was employed as an ensemble learning method that combines multiple decision trees to improve predictive stability and reduce overfitting. In this study, the number of trees was set to be 12, while all other parameters were retained at their default values. Selecting moderate number of trees represent pragmatic balance between model performance and computational efficiency and it consistent with exploratory predictive modelling practice (Hastie & Pregibon, 1992). The inclusion of Random Forest enable assessment of extent to which ensemble-based learning improve multiclass order status prediction relative to linear models.

3.7.5 Model Training and Validation Strategy

Model training and validation were conducted using Orange's Test & Score widget, following a standardized and reproducible evaluation protocol commonly adopted in applied predictive modeling research (Kuhn & Johnson, 2013).

Step 1: Validation Design

A stratified 10-fold cross-validation strategy were employed to preserving the class distribution of the multiclass target variable (order_status) across all folds.

Step 2: Unified Model Training

All classification algorithms were trained by using the same preprocessed dataset and identical validation setting to ensuring fair and unbiased comparison.

Step 3: Performance Measurement

Model performance were evaluated by using multiple metrics, including Area Under the ROC Curve (AUC), Accuracy (CA), Precision, Recall, F1-score, and Matthews Correlation Coefficient (MCC), which together provides comprehensive assessment of multiclass classification performance.

Step 4: Centralized Evaluation and Recording

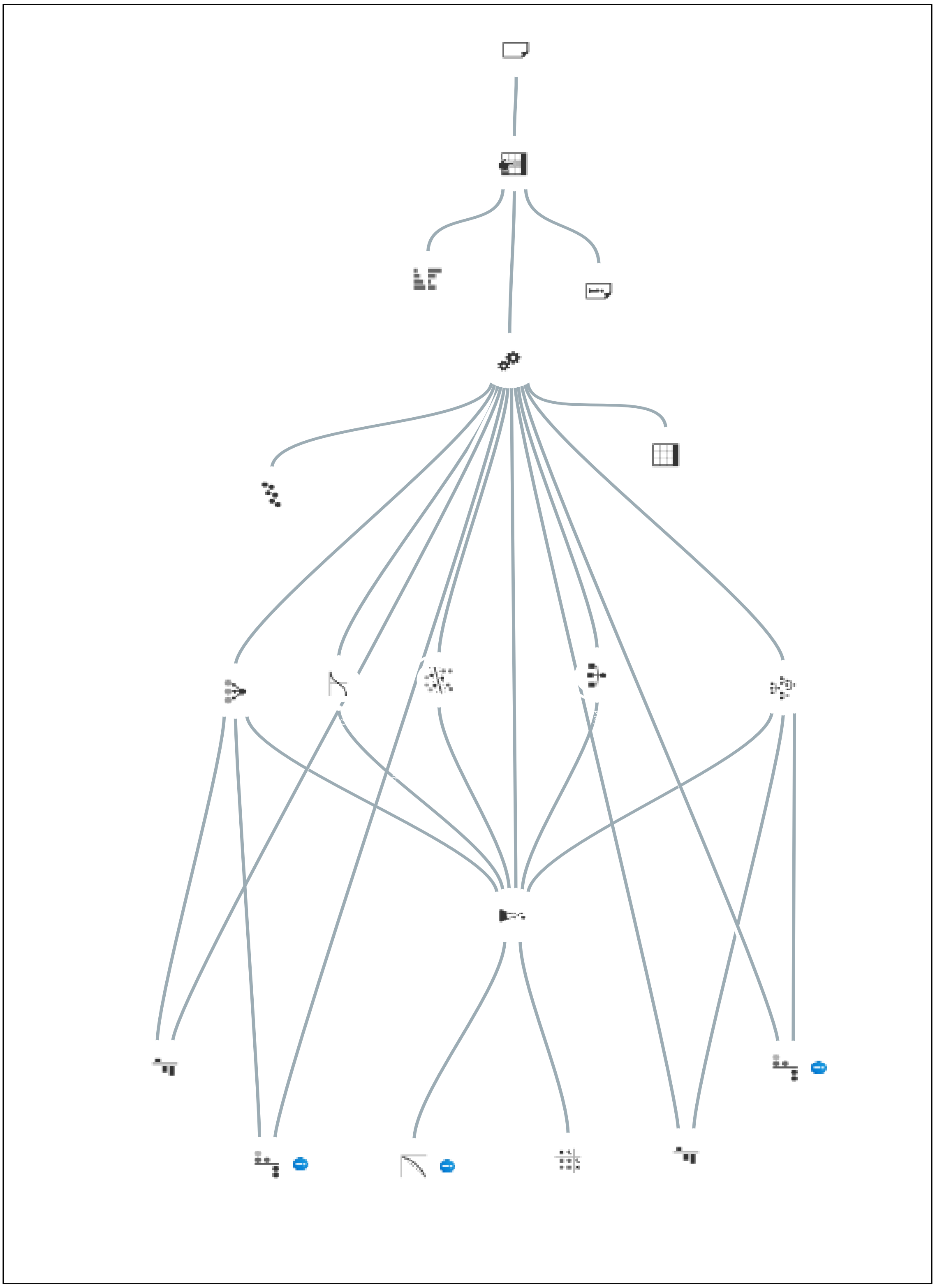
All evaluation metrics was computed and recorded in single validation framework, ensuring methodological transparency and repeatability of the training and validation processes.

3.7.6 Summary of the Predictive Modeling Procedure

This section summarizes the predictive modeling procedure implemented using the Orange platform. The algorithm modeling is attached in chart 1 next page. The process begins with loading and configuring the simulated transactional dataset, then feature selection and structured preprocessing to preparing the data for multiclass supervised learning. then Multiple classification algorithms with different modeling assumptions were trained by using unified preprocessing pipeline and evaluated under stratified cross validation framework. Model training and validation was conducted on a standardized and reproducible manner, ensure fair comparison across classifiers. Detailed performance results and model interpretation will be presented in the subsequent analysis chapter.

Chart 1

Algorithms Modeling



Chapter Four

Data Analysis and Results

4.1 Overview

This chapter present the empirical results derived from the analytical procedures outlined on Chapter 3. The analyses are conducted on structured sequence to ensuring clarity and methodological consistency. It start with descriptive examination of the dataset to summarizing the main transactional and customer-related characteristics. This is followed by a exploratory data analysis that aimed at identify primary patterns and association between key variables related to orders outcomes.

Subsequently, the chapter report the results for predictive modeling process implemented to classifying order outcomes. The performance of developed models are evaluated using the validation framework and classification matrix specified in the methodology chapter, allowing to a objective comparison of model effectiveness. The findings presented in this chapter is reported on a neutral and data-driven manner, without interpretative or theoretical discussion. A detailed interpretation of those results, along with their implications and comparison with prior studies, are provided in the subsequent discussion chapter.

4.2 Descriptive Analysis of the Dataset

4.2.1 Descriptive Statistics of Transactional Variables

This subsection present descriptive statistics for the main transactional variables included on t analysis, providing a overview of the dataset before conducting exploratory and predictive analysis. The descriptive statistics summarizes both of numerical and categorical variables, offering insight in the general structure and distribution of the transactional data without imply any causal relationships.

Table 4 report the descriptive statistics of the numerical variables. The table summarize the central tendency and dispersion of key transactional attributes, including delivery lead time, quantity, price, discount rate and order value. These statistics provide a initial understanding for the range and variability of transaction-level characteristics across the analyzed orders.

Table 4

Descriptive Statistics of Transactional Numerical Variables

Variable	mean	median	std	min	max
Delivery Lead Time (days)	3.64	4	1.53	2	14
Quantity	1.13	1	0.42	1	3
Price	256.03	255.28	141.26	10	499.98
Discount Rate	0.01	0	0.02	0	0.1
Order Value	284.61	267.32	195.58	9.35	1497.48

In additional to numerical variables, categorical transactional variables was examined by using frequency and percentage distributions. Table 5 present the distribution of payment methods across all orders, while Table 6 summarize the distribution of order status categories. As shown in Table 6, the dataset includes completed, returned, and canceled orders, reflect different order outcomes within the analyzed transactions.

Table 5

Payment Methods Distribution

#	Payment Method	Frequency	Percentage (%)
0	COD	22466	74.89
1	Card	4493	14.98
2	Wallet	1833	6.11
3	PayPal	1208	4.03

Table 6

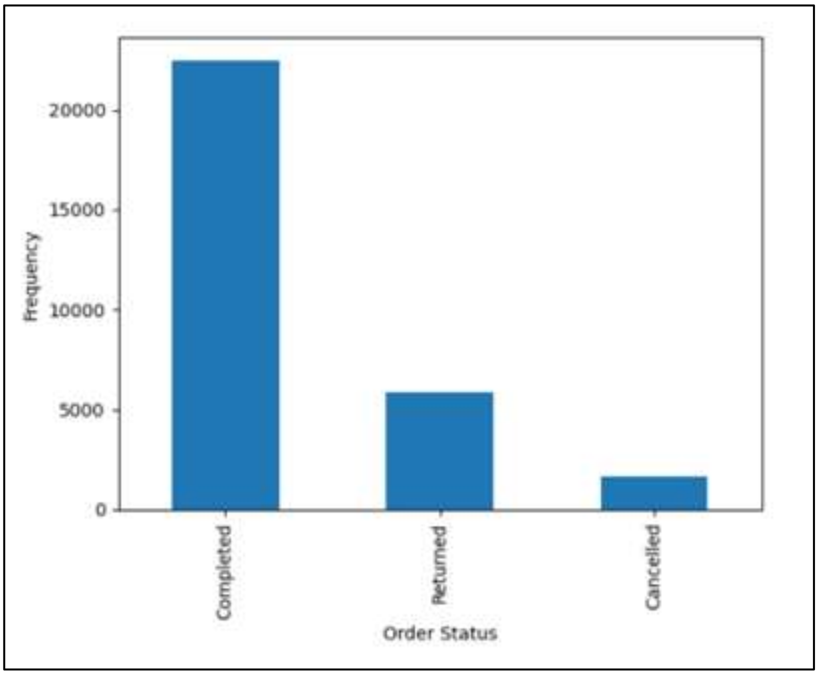
Order Status Distribution

#	Order Status	Frequency	Percentage (%)
0	Completed	22474	74.91
1	Returned	5876	19.59
2	Cancelled	1650	5.5

Figure 7 illustrate the frequency distribution of order status categories. The figure provide a visual representation of the relative occurrence for each order outcomes, complementing tabular distribution presented in Table 6. This visualization supports clear and concise overview of how orders is distributed across completion, return, and cancellation status within the dataset.

Figure 7

Distribution of Order Status



Overall, the descriptive analysis presented on this subsection established statistical baseline for the transactional data. The summarized distributions and frequency pattern serves as a foundation for subsequent exploratory data analyses and predictive modelling procedures presented on the following section.

4.2.2 Customer-Type Distribution (Q75-Based Classification)

This subsection describes the distribution for customer type based on the rule-based classification approach that derived from purchases frequency. Customers was classified to two categories—Regular and Premium—by using the 75th percentile (Q75) of the purchase frequency distribution as threshold. This classifications is applied to descriptive purposes only and doesn't represents a clustering or machine-learning–based segmentation techniques.

Purchase frequency were computed as the total number of orders steed by each customer during the study period. Based on ordered distribution of purchase frequencies, the computed Q75 value were equal **12 orders**, indicate that customers whose purchase frequency was equal to or above this threshold are belong to the upper quartile of the purchasing intensity. So, customers with twelve or more purchases were classified as Premium, and those below this threshold were classified as Regular.

Table 7 present the distribution of customers across those two categories. The results shows that the majority of customers falls in the Regular category, and while a smaller proportion was classified as Premium. This distribution provides an overview of purchasing intensity levels within the dataset and established a descriptive customer-type variable which is utilized in subsequent analyses.

Table 7

Customers Distribution

Customer Type	Number of Customers	Percentage (%)
Regular	2101	70.03
Premium	899	29.97

Overall, the Q75-based customer-type classification offer transparent and data-driven representation of customer purchasing intensity. The resulting categories serves as a descriptive inputs for later exploratory analysis and predictive modeling, without imply behavioral causality or customer segmentation beyond the applied distribution-based rule.

4.3 Exploratory Data Analysis

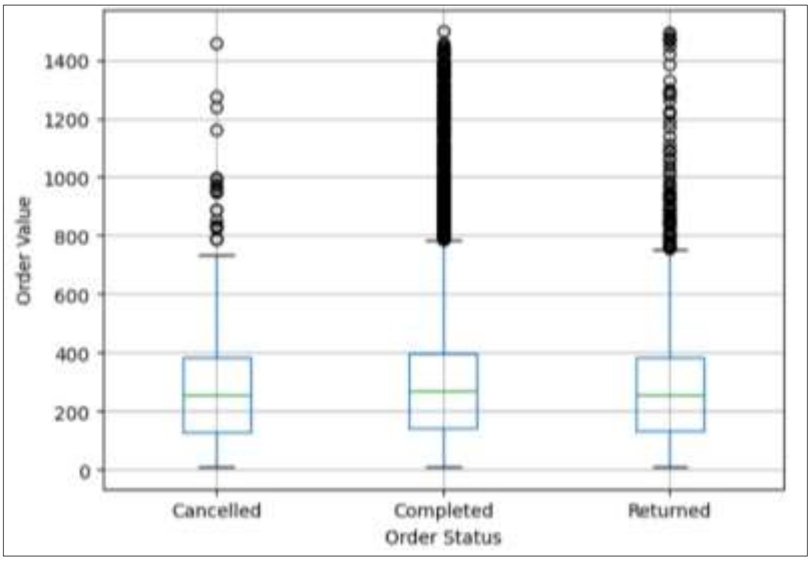
This section presents an exploratory analysis aimed at identifying preliminary patterns and associations between key transactional variables and order outcomes. The exploratory data analysis focuses on **order status** as the reference variable and examines how selected financial, logistical, and payment-related attributes vary across different order outcomes. The results presented in this section are descriptive and exploratory in nature and are intended to provide contextual insight prior to predictive modeling.

4.3.1 Order Value Across Order Status

Figure 8 illustrates the distribution of order value across different order status categories using a boxplot representation. The figure compares the central tendency and dispersion of order values for completed, returned, and canceled orders. The boxplot format enables a visual comparison of the median values, interquartile ranges, and the presence of extreme values across order outcomes. This visual exploration provides an initial indication of how order value distributions vary across different order.

Figure 8

Order Value by Order Status

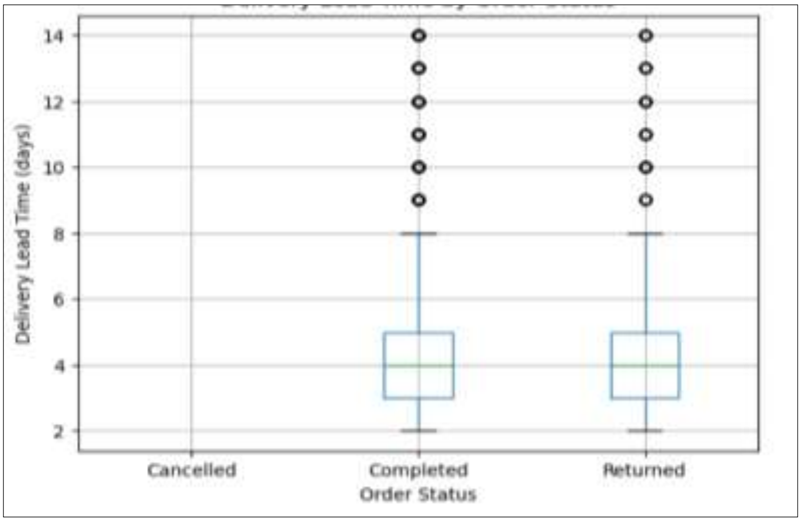


4.3.2 Delivery Lead Time Across Order Status

Figure 9 presents a boxplot comparison of delivery lead time across order status categories. The figure displays the distribution of delivery duration, measured in days, for completed and returned orders. The visualization highlights differences in the spread and central tendency of delivery lead times across order outcomes, offering an exploratory view of logistical characteristics associated with different order statuses. These observed patterns serve as descriptive insights that inform subsequent stages of analysis.

Figure 9

Delivery Lead Time by Order Status



4.3.3 Payment Method Patterns Across Order Status

To further explore transactional characteristics associated with order outcomes, a cross-tabulation analysis was conducted between payment method and order status. Table 8 reports the percentage distribution of payment methods within each order status category. The table provides a comparative overview of how different payment methods are represented across completed, returned, and canceled orders. This descriptive comparison supports an initial understanding of payment-related patterns in relation to order outcomes and complements the graphical analyses presented earlier in this section.

Table (8)

Distribution of payment methods within order status

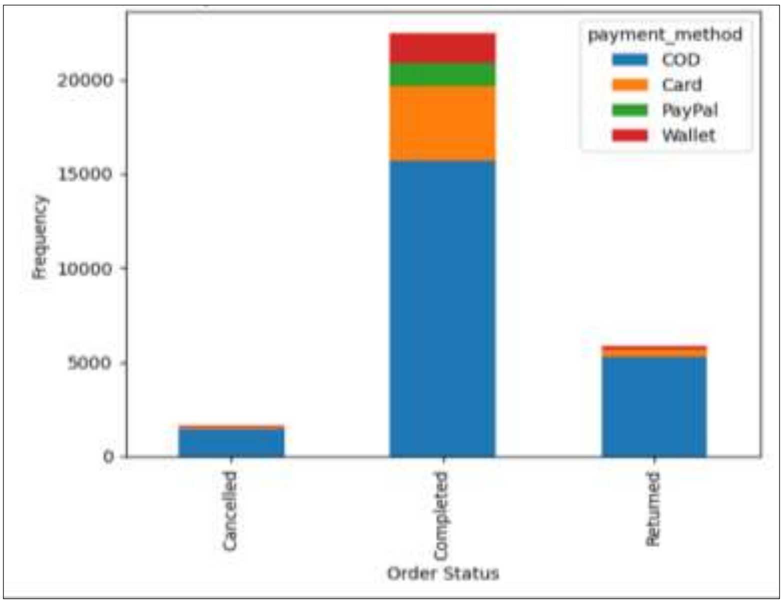
order_status **payment_method**	**Cancelled**	**Completed**	**Returned**
COD	89.82	69.83	90.03
Card	6.73	17.73	6.77
PayPal	0	5.38	0
Wallet	3.45	7.07	3.2

4.3.4 Payment Method Distribution Across Order Status

Figure 10 presents a stacked bar chart illustrating the distribution of payment methods across different order status categories. The figure provides a comparative visual overview of how payment methods are represented within completed, returned, and canceled orders. By displaying the composition of payment methods for each order outcome, the stacked structure facilitates an exploratory comparison of payment-related patterns across order statuses. This visualization complements the cross-tabulation results by offering an intuitive representation of relative distributions without implying causal relationships.

Figure 10

Payment Method Distribution Across Order Status



4.3.5 Customer Type Distribution Across Order Status

Figure 11 in appendix C, illustrates the distribution of order status categories across customer types, classified using the Q75-based purchase frequency threshold. The bar chart compares the frequency of completed, returned, and canceled orders for Regular and Premium customers.

This exploratory visualization provides an initial descriptive overview of how order outcomes are distributed across customer types, supporting the inclusion of the customer-type variable in subsequent analytical stages. The figure is presented for descriptive purposes only and does not imply behavioral or causal interpretations.

4.3.6 Order Outcome Rates by Customer Type (Q75-Based Classification)

Table 9 presents the distribution of order outcomes across customer types based on the Q75 purchase frequency classification. The table reports the percentage of completed, returned, and cancelled orders within each customer group. Observable differences can be noted between Regular and Premium customers, particularly in the distribution of completed and returned orders. This descriptive comparison provides additional context for understanding how order outcomes vary across customer types and supports the inclusion of customer-related variables in the predictive modeling stage.

Table (9)

Distribution of Order Status by Customers

customer_type_q75 order_status	Premium	Regular
Cancelled	2.71	7.46
Completed	89.12	64.92
Returned	8.17	27.62

4.3.7 Correlation Analysis for Exploratory Diagnostics

As part of the exploratory data analysis, pairwise Pearson correlation analysis was conducted to examine the underlying structure of the dataset and identify potential redundancy among explanatory variables. Given that the predictive models employed in this study are non-linear and probabilistic in nature, the analysis was used solely for diagnostic and interpretive purposes and did not influence model specification or performance.

Table 10

Pearson Correlation Matrix Between Key Numerical Variables

Variable	price	quantity	order_value	delivery_time	discount_rate
price	1.000	−0.002	**0.804**	0.001	0.003
quantity	−0.002	1.000	**0.517**	−0.009	**0.296**
order_value	**0.804**	**0.517**	1.000	−0.003	0.125
delivery_time	0.001	−0.009	−0.003	1.000	0.099
discount_rate	0.003	**0.296**	0.125	0.099	1.000

Table 10 shows the correlation analysis between numerical variables indicate that order value is strongly corelated with price (r = 0.804) and moderately corelated with quantity (r = 0.517), which is expected because of its derived nature. Quantity also shows a moderate positive correlation with discount rate (r = 0.296), suggesting that higher discounts is associated with bigger purchased quantities. All other pairs correlations, particularly that involving delivery lead time, are weak or negligible, indicating limited linear dependence among operation and transactional attributes.

Summary of Exploratory Findings

Overall, the exploratory data analysis highlights observable distributional differences in transactional and logistical variables across order status categories. These preliminary patterns provide descriptive context and justify the inclusion of the examined variables in the predictive modeling stage presented in the following section. The findings in this section are not interpreted as causal relationships but serve as an exploratory foundation for subsequent analytical procedures.

4.4 Predictive Modeling Results

This subsection provides a brief overview of the predictive modeling approach used to classify order outcomes based on transactional and customer-related data. Supervised classification models were developed in accordance with the methodological framework described in Chapter 3, with order status defined as the target variable.

The results reported in this section focus solely on model performance within the adopted validation framework. Interpretative analysis and discussion of implications are intentionally deferred to the subsequent chapter to maintain a clear distinction between results and discussion.

4.4.1 Model Training and Validation Setup

The predictive models were trained and evaluated using a stratified cross-validation framework to ensure robust and unbiased performance assessment. Specifically, stratified 10-fold cross-validation was employed, allowing the models to be trained and tested across multiple data partitions while preserving the original class distribution of the target variable in each fold. This approach is particularly suitable for classification tasks involving imbalanced order outcome categories.

All models were trained using the same preprocessed dataset and feature set to ensure fair and consistent comparison. Model performance was evaluated by averaging the results across all validation folds, thereby reducing the impact of random data partitioning and improving the reliability of the reported metrics.

To provide a comprehensive evaluation of classification performance, multiple metrics were employed, including Accuracy (CA), Precision, Recall, F1-score, Area Under the

ROC Curve (AUC), and Matthews Correlation Coefficient (MCC). The use of multiple evaluation measures enables a balanced assessment of model performance, particularly in scenarios where class imbalance may affect the interpretation of accuracy alone.

4.4.2 Model Performance and Comparative Analysis

This subsection presents the predictive performance results for the individual classification models that evaluated on this study and comparative evaluation. The comparison aims to identifying the model that demonstrate the most reliable and balanced predictive performance for classifies order outcomes under the adopted stratified 10-fold cross-validation framework based on the performance metrics reported in Table 11

Table (11)

Models Testing and Scoring

Model	AUC	CA	F1	Prec	Recall	MCC
Random Forest	0.835	0.795	0.785	0.78	0.795	0.453
Naive Bayes	0.847	0.717	0.738	0.78	0.717	0.415
SVM	0.43	0.654	0.62	0.631	0.654	0.023
Logistic Regression	0.809	0.782	0.732	0.722	0.782	0.32
Tree	0.683	0.778	0.772	0.767	0.778	0.417

To ensure a comprehensive and reliable evaluation of the predictive models, multiple performance metrics were employed. The Area Under the ROC Curve (AUC) was used to assess the models' overall discriminative ability between order status categories, independent of class distribution. Classification Accuracy (CA) provides a general measure of correctly classified instances, while Precision and Recall offer complementary perspectives on classification correctness and sensitivity. The F1-score was adopted as a balanced metric that jointly accounts for Precision and Recall, making it particularly suitable for imbalanced classification settings. In addition, the Matthews Correlation Coefficient (MCC) was reported as a robust indicator of overall classification quality, as it incorporates all elements of the confusion matrix and is less affected by class imbalance.

Overall, the results indicate noticeable variation in model performance across the evaluated metrics, highlighting differences in discriminative ability, classification balance, and robustness to class imbalance. Among the evaluated models, Random **Forest** and Naive Bayes achieved superior performance relative to the remaining classifiers, albeit with distinct strengths.

Random Forest

The Random Forest models demonstrated the most balance overall performance. It have achieved a high Accuracy of 0.795, accompanied by the highest F1-score 0.785 between all models, which indicating a strong balance between Precision and Recall. The model also attained a Recall value of 0.792, suggesting effective identification for order outcome categories, and a Precision of 0.778, reflect consistent classification correctness. Importantly, Random Forest have recorded the highest Matthews Correlation Coefficient (MCC) value 0.453, underscore its robustness in handling class imbalance. Although its AUC value 0.835 was slightly lower than that of Naive Bayes, its remained high, confirming strong discriminative capability. Collectively, those results identifying Random Forest as the most reliable and well-balanced predictive model on this study.

Naive Bayes

In other side, Naive Bayes classifier has exhibited the strongest discriminative performance, achieving the highest AUC values 0.847. This result indicates superior ability to distinguishing between different order status categories across decision thresholds. However, its overall Accuracy 0.717 and F1-score 0.738 was lower than of Random Forest, suggesting comparatively weaker balance between Precision and Recall. Despite this, Naive Bayes have maintained a relatively high Precision 0.780 and a solid MCC values 0.415, confirming its effectiveness as a competitive probabilistic classifier. Those findings positioning Naive Bayes as a strong complementary model, particularly is valued for its discriminative power.

Decision Tree

The Decision Tree model have achieved moderate performance across several metrics, with an Accuracy of 0.778, a F1-score of 0.772, and an MCC value of 0.417. While these values indicate reasonable classification capability, the model's AUC 0.683 were notably lower than of Random Forest and Naive Bayes, suggesting weaker overall discriminative ability and reduced generalization performance.

Logistic Regression

Logistic Regression have served as baseline linear classifier and produced moderate result, achieve an AUC of 0.809, Accuracy of 0.782, and F1-score 0.732. Although its performance were competitive on terms of Accuracy and Recall (0.782), the relatively lower MCC 0.320 indicate limited robustness when accounting for class imbalance, rendering its less effective than top-performing models.

Support Vector Machine (SVM)

Finaly, the Support Vector Machine (SVM) model yielded the weakest performance between all evaluated classifiers. It has recorded low AUC of 0.421, an Accuracy of 0.654, and an MCC value closes to zero 0.023, indicate near-random classification behavior. Those results suggest that the SVM model wasn't well-suited for the characteristics of the analyzed dataset.

Based on the comparative analysis, Random Forest is identified as the most suitable model for the predictive task on this study because of its consistently strong and balance performance across multiple evaluation metrics. Naive Bayes are retained as a complementary model, and given its superior discriminative capability as reflected by highest AUC value. ROC analysis further supports the comparative evaluation of the models by illustrate their discriminative performance across decision thresholds. The observed ROC curves are consistent with the reported AUC values, confirming the superior discriminative capability of Random Forest and Naive Bayes as it shown on figure 12 in appendix C.

Those findings provide a clear and data-driven basis for model selecting and form the foundation for further interpretation on the subsequent discussion chapter.

4.4.3 Confusion Matrix Analysis

To more investigate the classification behavior of the predictive model beyond aggregate performance metrics, confusion matrix analysis were conducted for the two best-performed models that identified on the previous section, namely Random Forest and Naive Bayes. The confusion matrix provide class-level perspective on model predictions by illustrate the distribution of correct and incorrect classifications across orders status categories.

Random Forest

Figure 13 in appendix C, present the confusion matrix of the Random Forest model. For the *Returned* order category, the model correctly classified 2,193 out of 5,876 returned orders. However, a substantial number of return orders (3,683 instances) was misclassified as *Completed*, indicating a relatively conservative prediction behavior to this class. This pattern suggests that while Random Forest perform good on minimizing overall misclassification errors, it exhibits lower sensitivity on identify returned orders.

In contrast, the model has demonstrated strong performance to the *Completed* category, correctly predicting 20,018 of 22,474 completed orders. As well as, for the *Cancelled* orders, Random Forest correctly have classified 1,561 out of 1,650 instance, with just a limited number of misclassifications. Those results highlights the model's robustness and stability across majority classes, that's consistent with its high overall Accuracy 0.792 and MCC 0.446 reported earlier.

Naive Bayes

Figure 14 in appendix C, illustrate the confusion matrix for the Naive Bayes model. Notably, Naive Bayes have exhibited substantially higher sensitivity on identify Returned orders. The model correctly has classified 3,633 of 5,876 returned orders, significantly outperforming Random Forest on terms of recall to this specific class. The number of returned orders misclassified as Completed were reduced to 1,577, reflect a more sensitive classification behavior toward return-related patterns.

However, that increased sensitivity have came at the cost of higher misclassification rates to the other classes. For instance, Naive Bayes correctly classified 16,912 of 22,474 completed orders, that's notably less than the corresponding performance of Random Forest. Similarly, only 951 out of 1,650 canceled orders was correctly identified, indicate reduced precision to this category. Those patterns explain the lower overall Accuracy (0.717) and F1-score (0.738) of Naive Bayes, despite their superior discriminative performance that reflected by the highest AUC value (0.847).

Comparative Interpretation

The confusion matrix analysis reveals complementary strength between the two models. Random Forest demonstrate strong and stable performance across majority class, minimize overall classification errors and achieving balanced predictive behavior. on contrast, Naive Bayes show enhanced sensitivity on detect returned orders, a critical minority class in the context of order outcome prediction.

Those findings indicates that while Random Forest is more suitable as a primary predictive model because of its balanced performance, Naive Bayes provide valuable addition insight by effectively identify returned orders. The complementary behavior observed during confusion matrix analysis highlight the importance of class-level evaluation and support the potential benefits of employ multiple models to addressing different analytical objectives in the same predictive framework.

4.4.4 Feature Importance Analysis

To assessing the relative contribution of explanatory variables for the predictive performance of the classification models, a permutation-based feature importance analysis were conducted by using the Area Under the Curve (AUC) as the scoring metric. This approach evaluate the decrease on model discriminative ability when the values of each feature is randomly permuted, thereby quantify the importance of each predictor on distinguishing between returned and non-returned orders.

Feature Importance Results: Random Forest Model

The feature importance results for the Random Forest model, is illustrated in Figure 15 in appendix C, indicates a clear dominance for delivery-related and monetary variables on influence model performance. between all predictors, delivery lead time have emerged as the most influent feature, producing the largest decrease in AUC when permuted. This result suggest that the model rely heavily on delivery duration information to discriminating between order outcomes.

Following the delivery lead time, price and order value was ranked as the second and third most important predictors, respectively, highlighting the substantial contribution of transaction-related variables for the model's predictive capability. on contrast, categorical attributes like product category (Sports) and payment method (COD) exhibited moderate important, while customer segmentation and seasonal indicator (e.g., customer type: Regular, Season: Summer, Autumn, Spring) has showed comparatively lower contributions for the overall model performance.

Overall, the Random Forest model demonstrate feature important structure that characterized by a strong concentration of predictive power in a small subset of key variables, with a gradual decline on importance across the remain features.

Feature Importance Results: Naïve Bayes Model

The feature importance analysis to the Naïve Bayes model, is presented in Figure 16 in appendix C, reveal a different distribution of predictor contributions compared to the Random Forest model. While delivery lead time days remains the most influential features, its dominance are less pronounced, and the overall importance are more evenly distributed across multiple variables.

Customer-related attributes, particularly customer type (Regular) and customer type (Premium), ranked among the most influential predictors in this model.

Additionally, discount rate demonstrated a substantial contribution for the Naïve Bayes model's discriminative performance, that exceeding its relative importance observed in the Random Forest model.

Product category indicators (e.g., Sports) and payment related variables, include payment method (COD, PayPal, Card), has contributed modestly for the model's AUC, while other category-level variables (e.g., Fashion, Grocery) has exhibited limited influence. This pattern suggest that the Naïve Bayes classifier leverage a broader combination of behavioral, customer, and promotional features instead than relying predominantly on a small set of dominant predictors.

Comparative Observation of Feature Importance Patterns

A comparison of feature importance distributions across the two models indicate notable differences on how predictive information are utilized. The Random Forest model concentrate its predictive strength in a limited number of high-impact variables, particularly delivery lead time and monetary attribute. In contrast, the Naïve Bayes model distribute importance more evenly across customer characteristic, variables related to discount, and transaction features.

These differences reflect variation on the internal learning mechanisms of the two classifiers and provides a foundation for more interpretation for model behavior and practical implications, that's addressed in the subsequent discussion chapter.

4.4.5 Model Explainability Analysis

To enhancing the interpretability of the predictive models, an explainable AI analysis was conducted by using the *Explain Model* tool, focus specifically on the Returned class. This analysis examines the direction and magnitude of each feature's contribution for the model output, indicate whether high or low feature values increase or decrease the likelihood of a order being to classified as returned.

Explain Model Results: Random Forest

The explainability result for "return order" to the Random Forest model, that illustrated on Figure 17 in appendix C, indicate heterogeneous patterns of feature influence in returning predictions. Customers' variables, particularly customer type, exhibits asymmetric effect, where higher values associated to Regular customers tends to contributing positively toward the returned class, while Premium customers show a comparatively reduced positive impact.

Promotional and categorical variables also demonstrate noticeable effects. Higher discount rate values are associated with an increased contribution toward the returned outcome, while the Sports product category exhibits a positive directional impact on return predictions. In contrast, delivery lead time days shows dispersed impacting pattern, that indicating variability on how delivery duration contributes to returning classification across different observations.

Payment-related and monetary variables, include payment method (COD), order value, and price, displays moderate but mixed directional effects. Those features contribute to model predictions on both positive and negative directions, suggesting interaction effects instead than a uniform influence for the returned class. Variables as Fashion category and quantity demonstrate comparatively limited impacting on the overall model output.

Explain Model Results: Naïve Bayes

The explainability analysis for "return order" to the Naïve Bayes model, that shown in Figure 18 in appendix C, reveal a more structured and directional consistent pattern from feature influence.

Customer type emerges as a dominant explanatory variable, with Premium customers exhibit a stronger negative contributing to the returned class, while Regular customers contribute positively toward return classification.

Delivery-related and promotional factors maintain notable influencing. Higher values of delivery lead time days is associate to increased likelihood of a order that being classified as returned, while discount rate demonstrate a clear positive contribution when it elevated. Payment methods, particularly COD, exhibits a directional effect favoring the returned class, even with lower magnitude comparing to customer and delivery attributes.

Product category indicators, include Sports, Fashion, Grocery, and Toys, contributes modestly to the model output, primarily exhibiting negative or near-neutral effects. Generally, the Naïve Bayes model reflect a clearer separation of feature impacting, with fewer overlape contribution patterns compared to the Random Forest model.

Comparative Explainability Analysis for Cancelled Orders

To examining how predictive models internally differentiates cancelled orders of other order outcomes, an explainability analysis were conducted for the Cancelled target class by using both of Random Forest and Naïve Bayes classifiers. This comparative analysis focus on the direction and magnitude for feature contributions for the cancellation prediction, and providing insight to how each model operationalizes transactional and operational information.

Across both models, delivery lead time days emerges as the most influent explanatory variable of cancellation behavior. However, the nature of their contribution differs between the two classifiers. In the Random Forest model, delivery lead time exhibit a relatively concentrated positive impacting, with higher values contributing strongly toward the cancelled class for a subset of observations. In other side, the Naïve Bayes model display a more uniform distributed and directionally consistent positive contributing, and indicating a stronger linear association between longer delivery duration and order cancellation. See figure 19 in appendix C.

Customer-related variables show diverging and contribution structures across models. In the Random Forest model, customer type (Regular) and customer type (Premium) demonstrates relatively limited and near-neutral impacting for cancellation predictions. Oppositely, on the Naïve Bayes model, customer type play more pronounced role, with Regular customers is contributing positively in cancellation likelihood, while Premium customers exhibit a negative or neutral contribution pattern.

Features to related Promotion and payment also reveals model-specific differences. The discount rate displays minimal directional influencing on the Random Forest model, while on the Naïve Bayes model, higher discount values is associated with a clearer contribution to cancellation. Similarly, payment method (COD) exhibits a weak and mixed effecting on the Random Forest classifier but show more consistent negative-to-neutral impacting on the Naïve Bayes model.

Monetary variables like order value and price demonstrates limited explanatory power of cancellation in both of models, with clustered contributions close to zero, suggest that those features play a secondary role on cancellation decisions relating to operational and customer-related attributes. Product category indicators, include Sports and Grocery, contributes marginally across both of classifiers, with slightly more dispersed effects observed on the Naïve Bayes model.

Generally, the Random Forest model exhibit more localized and interaction-driven explainability pattern, that cancellation predictions is influenced by a small number of observations of high impact, particularly that related to delivery lead time. In contrast, the Naïve Bayes model demonstrate broader and more systematic feature contributions, with clearer directional effecting across customer type, delivery duration and promotional variables.

Those findings highlights how different modeling assumptions forms the internal decision logic of cancellation prediction, and providing a complementary perspective for the aggregating performance metrics and feature importance results that presented previous on this chapter.

4.4.6 Summary of Predictive Modeling Results

This chapter have evaluated multiple supervised classification models to predicting order outcomes by using stratified 10-fold cross-validation. The comparative results has demonstrated that Random Forest have achieved the most balanced all performance via key evaluation metrics, including Accuracy, F1-score, and MCC, and indicating robust and reliable classification behavior. In other side, Naive Bayes have exhibited superior discriminative capability, as reflected by the highest AUC value, and it showed greater sensitivity on identify returned orders.

Confusion matrix analysis also revealed complementary strengths between the two models, where Random Forest have provided stable performance across majority classes, while Naive Bayes more effectively have captured returned orders. Generally, the feature importance and explainability analyses consistently highlights delivery lead time days as the most influent operational factor across both of predictive models and outcome classes, then followed by selected transactional variables. While the Random Forest model concentrate predictive influence in a small subset of high impact variables—particularly delivery duration and monetary attributes—, the Naïve Bayes model distribute feature contributions more evenly across customer type, promotional and transactional features.

Explainability results further reveals that cancellation behavior are basically associated to pre-fulfillment factors, while return behavior are driven by post-fulfillment operational conditions. Collectively, those findings demonstrates that business intelligence–driven models can effectively differentiate order outcomes by leverage a combination of operational, transactional, and customer-related signals, and providing transparent and interpretable decision support to e-commerce operations.

Overall, the findings established a clear basis to selecting Random Forest as the basic predictive model, while highlighting the potential value of Naive Bayes as complementary classifier. Those results provide a concise foundation to the interpretative discussion that presented in the subsequent chapter.

Chapter Five

Discussion of Results

5.1 Overview

This chapter provides an interpretative discussion of the empirical findings presented in Chapter Four, with the aim of situating the observed results within the study's theoretical, methodological, and contextual foundations. The discussion focuses on explaining *why* specific patterns of order completion, cancellation, and return emerged, and *how* these patterns can be understood in light of Behavioral Decision Theory, trust- and risk-based perspectives, and the operational realities of the Palestinian e-commerce environment. The chapter systematically aligns the analytical results with the research questions, integrating insights from descriptive analysis, predictive modeling, and model explainability to develop a coherent narrative that links consumer decision-making under uncertainty with observable transactional outcomes. In doing so, the discussion bridges theory and practice by highlighting the analytical significance of the findings, their methodological implications—particularly regarding the use of synthetically generated data—and their relevance for business intelligence–driven decision support in data-constrained e-commerce markets.

5.2 Interpretation of Key Findings in Relation to Research Questions

5.2.1 Discussion of RQ1

What transactional and operational factors are most strongly associated with online order cancellation and return behavior, based on descriptive and predictive analytics?

The first research question aimed to identify the transactional and operational factors most strongly associated to order cancellation and return behavior. The empirical results reported in Chapter Four demonstrate that adverse order outcomes occur as structured behavioral responses to perceived risk and operational uncertainty and fulfillment-related frictions. Delivery lead time stood out as the primary predictive factor throughout descriptive analysis and feature importance results and model explainability outputs, which proved that logistics performance functions as the main element that determines customer behavior after their purchase.

The main factor that determines delivery times follows the principles of Behavioral Decision Theory according to its assertion that consumers make decisions based on limited information while they continually evaluate their options on situations with uncertain outcomes and possible financial losses. (Dominic & Pardamean, 2023). In online shopping environments delivery delay serves as a major uncertainty factor because it raises waiting costs to customers while destroying their trust on order fulfillment. Prior research demonstrates that unreliable or prolonged delivery times elevate perceived transaction risk and reduce expected utility, prompting corrective behavioral responses (Donker et al., 2025; Sun & Chen, 2025). In this context, an interpretation of decisions of cancellation and return can be "rational adaptations" to adverse updates on perceived risk, instead of markedly irrational or impulsive behavior.

The study results demonstrate two separate processes which lead to cancellations and returns. Cancellations happen mainly because customers end their orders before delivery because they expects their products to arrive later than scheduled. The pattern corresponds with existing research which show cancellations happen when customers lose interest on their order and the status of their product remains unconfirmed until delivery. (El Kihal et al., 2025). Returns show the results of customer assessment which evaluates delivery performance and product experience against their expectations. Customers who experienced dissatisfaction with their purchase decided to returning the items. (Z. Chen et al., 2023; Donker et al., 2025). The empirical separation that observed between those outcomes support the conceptual distinction emphasized in post-purchase behavior research.

The study found that monetary variables which included price and order value showed significant connections for order outcomes yet their impact remained weaker than delivery-related factors. The research showed that higher-value orders demonstrated increased reaction to operational changes because financial exposure brought about greater loss aversion which impacted customers after they made their purchases. The research shows that people respond to service failures based on their perceived loss size because this environments lacks proper consumer protection and their enforcement systems are ineffective (Mofokeng, 2023; Sun & Chen, 2025).

Payment method further contributed to explaining variation on cancellation and return behavior. Orders that placed by using cash-on-delivery exhibited higher volatility relativing to prepaid digital payment methods. This pattern align with prior evidence from emerging markets that indicating that COD functions as a risk-reduction mechanism on low-trust environments by postponing financial commitment until delivery (Aish & Noor, 2025; NAZZAL et al., 2021). However, by reducing upfront commitment and switching costs, COD simultaneously increase the likelihood of cancellation or refusal when uncertainty persists. This findings reinforces trust- and risk-based models on e-commerce, which emphasizes that payment mechanisms shape post-purchase stability in addition to adoption intentions (Aish & Noor, 2025; Belmonte et al., 2024).

The study found that customer heterogeneity served as a crucial factor that explained customer behavior patterns. The Q75-based classification showed that regular customers exhibits higher variability on cancellation and return behavior comparing to premium customers. This pattern is consistent with research demonstrating that accumulated transaction history and purchasing frequency stabilizes consumers behavior by reducing informational asymmetries and strengthening relational trust (El Kihal et al., 2025; Mofokeng, 2023). Frequent customers, after they developed experiential knowledge and confidence on the seller's fulfillment process, display lower sensitivity to short-term uncertainty, while infrequent customers remain more susceptible for reassessment and abandonment.

Collectively, the findings addressing RQ1 suggest that order cancellations and returns represents rational, risk-sensitive behavioral outcomes shaped by operational conditions not isolated service failures. The main role of delivery lead time, beside to the moderating effects of payment method, order value, and customer type, underscore the importance of analyzing post-purchase behavior via an integrated behavioral–operational lens. This results corroborates prior literature that emphasizing the value of transaction-level data and predictive analytics to uncovering revealed consumer behavior on e-commerce settings that characterized by uncertainty and data constraints (Donker et al., 2025; Stylianou & Pantelidou, 2025b).

The complete distribution of return reasons supports the results of behavioral analyses which the predictive model established. The returned orders showed equal distribution between product-related and preference-based reasons which included "not as described" 26.12% "defective" 24.76% "no longer needed" 24.73% and "missing or wrong item" 22.92% while "slow delivery" emerged as the least mentioned reason at 1.46%. The study results matchs previous e-commerce research which demonstrated that customers uses logistical delays as hidden behavioral triggers rather than writing it as official return explanations. (Z. Chen et al., 2023; Donker et al., 2025; Sun & Chen, 2025). Delivery-related uncertainty affects post-purchase decision-making because it creates more challenges to understand delivery times yet customers handle their product returns by using product- or preference-based explanations which sound more valid and practical (Dominic & Pardamean, 2023; El Kihal et al., 2025). The delivery lead time establishes a strong connection to delivery related behavior patterns which people use to justify their choice of return explanation yet the general population considers "slow delivery" to have little value as an official return reason. The operational predictors and diagnostic return reasons show complete alignment with each other which demonstrates that the simulated data can accurately predict behavioral patterns in e-commerce while also serving as a diagnostic tool for data-scarce online retail environments.

5.2.2 Discussion RQ2

To what extent can synthetically generated data, when theoretically grounded and analytically validated, represent realistic patterns of online consumer behavior in data-constrained markets such as Palestine?

The second research question examine whether synthetically produced transactional data can accurately simulate actual online shopping patterns on Palestinian data-restricted environments. The examination of this research question doesn’t focus on replicating actual statistical data but assesses whether the produced data maintain behavioral patterns and theoretical relationships and support analysis during both of descriptive and predictive methods. The results presented on Chapter Four demonstrate via various proofs that the synthetic dataset reaches a degree of authenticity necessary for use in both diagnostic and predictive business intelligence functions.

The final outcome distributions showed their actual behaviors because of the implementation of rule-based restrictions which served as the key measure for assessing the authentic levels of behavioral realism. The simulation design have established initial base rates for completed, returned, and cancelled orders which later changed because of rules that scientists developed to study customer loyalty and discount usage and seasonal patterns and delivery efficiency. The observed deviations from expected outcomes don't indicate simulation errors because they demonstrate how consumer behavior interact with operational conditions which researchers have documented on e-commerce studies. The previous research show that when organizations establish behavioral and operational limitations, organizations will experience changes in their marginal distributions because customers will modify their behavior. (Donker et al., 2025; Stylianou & Pantelidou, 2025b). The fact that outcome distributions adjusted on a logically consistent manner so supports the internal behavioral validity of the synthetic data.

The evidence of realism in the study comes from the verification that descriptive patterns match the results of predictive modeling. Theoretical explanations of post-purchase behavior in online retail environments use the same variables which emerged as important predictors including delivery lead time and customer type and monetary attributes. Delivery-related uncertainty has been identified multiple times as the main factor which leads people to cancel their orders and return their products because it determines their assessment of risk and their post-purchase satisfaction. (Donker et al., 2025; Sun & Chen, 2025). The relevance of this variable on the feature significance and interpretability analyses indicate that the synthetic data retain important behavioral signals, rather than simply random correlations.

The synthetic data maintains its validity because the predictive models show both consistent performance and their results can be explained through their stable performance. The data shows structured information because multiple classifiers can accurately identify completed and cancelled and returned orders through their ability to do so while showing specific feature importance and explainability patterns. Prior methodological studies on synthetic data emphasizes that analytical validity should be evaluated according to a dataset's capacity to support meaningful inference and prediction, better than on exact duplication of real-world records (Drechsler, 2011; Sanchez-Serrano et al., 2025). In this study, The synthetic dataset meet these requirements because it provides both of descriptive diagnostic tools and predictive modeling capabilities that follow established behavioral theory.

The research demonstrates that synthetic data which have been developed through theoretical foundations and through analytical verification can serve as a substitute for actual transaction data in Palestine's data-restricted markets. The data provides strong support for business intelligence projects which require exploratory research and diagnostic analysis and decision-making model development because actual data from the field cannot be used to establish causal relationships. The study results which address research question two show that synthetic transactional data which researchers developed through rigorous design and validation methods can accurately model actual online consumer patterns for analysis purposes in both emerging and restricted e-commerce marketplaces.

5.2.3 Discussion of RQ3

How effective are business intelligence–driven predictive models in identifying and forecasting orders likely to be cancelled or returned?

The third research question evaluates the effectiveness of business intelligence–driven predictive models in identifying and forecasting orders that are likely to be cancelled or returned. Chapter Four results show that supervised classification models embedded in a structured BI workflow successfully identify predictive signals from transactional and operational data when real-world datasets are unavailable. The study evaluates model effectiveness through two assessment methods which measures overall accuracy and model performance in handling class discrimination and different class sizes and model interpretability in situations with multiple classes and unbalanced outcomes.

The Random Forest classifier achieved the most balanced overall performance across Accuracy, F1-score, and Matthews Correlation Coefficient (MCC). This align with prior research indicating that ensemble-based methods is particularly effective on modeling complex, non-linear interactions between operational, monetary, and customer-related variables on e-commerce contexts (Esmeli et al., 2022; Stylianou & Pantelidou, 2025b). The strong MCC performance further suggests robustness to class imbalance, a critical requirement when predicting relatively infrequent but operationally costly outcomes like cancellations and returns (Donker et al., 2025).

In contrast, the Naive Bayes classifier demonstrated the highest Area Under the Curve (AUC) and superior sensitivity on identifying returned orders. Even its overall accuracy were lower than that of Random Forest, it classified a larger proportion of minority-class return cases correctly. This behavior matches with the probabilistic structure of Naive Bayes, which shows a tendency to prefer detecting minority classes while sacrificing detection accuracy for majority classes (X. Chen, 2025). In the context of e-commerce operations, this trade-off is analytically meaningful, as the cost of failing to identify high-risk return orders may outweigh the cost of conservative over-flagging.

The two models demonstrate their combined strength to showing that prediction accuracy depend on the specific analysis purpose. Random Forest offer reliable forecasting results which maintains consistent performance cross operational monitoring tasks, while Naive Bayes improve the detection of orders that show a high likelihood of return. The decision analytics literature show that different modeling assumptions lead to different results, which the two models demonstrate through their complementary nature. (Günther et al., 2017; Stylianou & Pantelidou, 2025b).

Feature importance and explainability analyses further supports predictive validity. Delivery lead time consistently have emerged as the most influential predictor across models, it followed by selected monetary variables and other related to customers. This convergence between empirical importance and established theoretical drivers—like fulfillment reliability and customer experience—reinforce behavioral realism (Donker et al., 2025; Sun & Chen, 2025).

Also, the models meaningfully recognized between cancellation and return behavior. Cancellation predictions were driven basically by uncertainty of pre-fulfillment, particularly delivery-related factors, while return predictions reflected a broader combination of operational, monetary, and customer-related influences. This distinction matches with post-purchase behavior research that conceptualizes cancellations as late-stage uncertainty and returns as outcomes of post-delivery dissatisfaction and unmet expectation (Z. Chen et al., 2023; El Kihal et al., 2025).

In general, the findings indicates that BI-driven predictive models is capable to effectively identify and predict order outcome risk when it's supported by suitable validation and interpretation mechanisms. While no single model outperforms all metrics, combining ensemble and probabilistic approaches enhance both of stability and sensitivity, thus powering decision support for managing post-purchase risk within data-constrained e-commerce environments.

5.2.4 Discussion of RQ4

How can insights derived from descriptive and predictive analytics be operationalized within a business intelligence framework to support data-driven decision-making in e-commerce operations?

The fourth research question focused on how insights generated from descriptive and predictive analytics can be translated into actionable decision-support mechanisms in a business intelligence framework. The study demonstrates that analytical outputs which include descriptive patterns and predictive risk estimates and model explainability results can be utilized to support fundamental e-commerce decision-making processes instead of serving as diagnostic tools.

At the descriptive level, distributional analyses of order outcomes, payment methods, customer types, and delivery performance provide a foundational monitoring layer for business intelligence systems. These descriptive indicators enable continuous tracking of operational stability and customer behavior, allowing managers to identify emerging risk patterns, such as rising return rates within specific customer segments or delivery windows. Prior BI research emphasizes that such descriptive dashboards constitute a critical first step in transforming raw transactional data into managerial awareness (Günther et al., 2017; Stylianou & Pantelidou, 2025b).

At the predictive level, embedding model outputs—like order-level risk scores—in BI systems allow proactive determination of orders that exposed to cancellation and return. This allows firms for implement targeted interventions (e.g., delivery prioritization or customer communication), matching with evidence on the anticipatory value of predictive analytics on online retail operations (Donker et al., 2025).

Explainability results more enhance implementation by clarify the drivers of risk. The consistent importance of delivery lead time, customer type, and monetary exposure support focused policy design instead of common rules. This targeted approach reflect previous findings that operational transparency improves fulfillment reliability and risk management (El Kihal et al., 2025; Sun & Chen, 2025).

Overall, integrating each of descriptive diagnostics, predictive modeling, and interpretability in a unified BI framework support a transformation from reactive to proactive post-purchase management, particularly on data-constrained environments like Palestine.

5.3 Theoretical Implications

The results of this research lead to multiple theoretical consequences which impacts the research of online shopping behavior in e-commerce settings that lacks sufficient data and face uncertain conditions:

- The results validate Behavioral Decision Theory because they demonstrate that consumer behavior of cancellations and returns functions as adaptive risk management which operates during the entire transaction process as consumers evaluate their anticipated benefits.
- The results show that cancellations and returns represent two different concepts because cancellations occur when customers face uncertainty before their orders get delivered while returns happen when customers assess their received items and discover they don't meet their expected standards.
- The research expand existing trust and risk assessment frameworks by proving that delivery reliability operational elements serve as the primary drivers of human behavior.
- The study highlights the limitations of purely attitudinal models and supports outcome-oriented behavioral framework grounded on revealed behavior by analyzing observed order outcomes instead of self-reported intentions,.
- Integrating BI-driven predictive analytics contributes theoretically by showing how explainable predictive models can detect inherent behavioral structures, thus powering the link between behavioral theory and empirically observed consumer actions.

5.4 Practical Implications

The findings of this study demonstrate multiple practical implications for e-commerce operations and managerial decision-making, especially on data-constrained and operationally uncertain markets:

- Delivery lead time emerged as a critical operational risk indicator, which suggesting that improve reliability of fulfillment—especially for orders that high-value or time-sensitive— that can reduce cancellation and return rates.
- Predicting the risk of cancellation or return for each order helps companies act early before shipping, like speeding up delivery, contacting the customer in advance, or confirming payment detail.
- Distinguishing between orders that exposure to cancellation and return supports more specific control: cancellations require processes before shipment, while return risk can be reduced by better order accuracy and forecast management.
- Customer segmentation results indicates that customers exhibit higher behavioral changes, meaning that different operational strategies could enhance efficiency. Premium customers might require fewer control mechanisms, and regular customers might benefit from additional fulfillment safeguard.
- Payment method—especially cash-on-delivery—work as a signal of lower transactional commitment, and integrating indicators such that in dashboards can enhance risk anticipating.
- Embedding each of descriptive analytics, predictive score, and explainability within a BI framework supporting a shift from reactive handling to proactive, data-driven coordination across inventory, logistics, and returns managing.

Chapter Six

Conclusion and Recommendations

6.1 Conclusion

The study has examined online orders outcomes on the Palestinian e-commerce context by using a business intelligence–driven analytical framework, focus on order completion, cancelation, and return behaviors as observable post-purchase outcomes instead of stated purchase intentions.

The findings demonstrates that order cancelations and returns aren't random event, but structured behavioral response for identifiable operational and transactional conditions.

Delivery lead time have emerged as the most influent operational factor across all analytical stages, and confirming its central role on forming both cancelation and return behavior on data-constrained and operationally uncertain e-commerce environments.

The results reveal clear behavioral distinction between cancelation and return outcomes:

- Orders cancellations primarily reflect pre-fulfillment uncertainty and late-stage reassessment be for shipment.
- Product returning represent post-fulfilment evaluation and expectation disconfirmation after delivery.

Payment method was shown to influencing order outcomes stability, with cash-on-delivery transactions exhibiting higher behavioral volatility compared for prepaid digital payment methods.

Customer purchasing intensity play moderating role on post-purchase behavior, as frequents customers demonstrates more stable order outcomes and lower sensitivity to operation uncertainty than regular customers.

The study confirms that theoretically grounded and analytically validated synthetic data can represents realistic patterns of online consumer behavior and supporting meaningful descriptive and predictive analysis on contexts where accessing to real transactional data are limited.

Predictive models embedded in a business intelligence framework exhibited consistent and interpretable performance, demonstrate the feasibility of forecasting cancellation and returning risk by using observable transactional and operational signals.

Overall, the study conclude that integrate descriptive diagnostics and predictive analytics in a business intelligence framework provide a robust foundation for proactive, data-driven decision-making on the Palestinian e-commerce context, with a clear shift from reactive management toward anticipatory operation control.

6.2 Recommendations

6.2.1 Recommendations for E-Commerce Operations

- Treat delivery lead time as primary operational risks indicator and integrating it to daily order monitoring processes in order to anticipating potential cancelations and returns before fulfillment.
- Differentiate operational handling between cancelation-prone and return-prone orders, recognize that each outcome reflect a distinct stage on the transaction lifecycle and requires different intervention strategies.

6.2.2 Recommendations for Business Intelligence Implementation

- Integrate predictive model outputs, like order-level risks scores, to operational BI dashboards to supporting proactive decision-making instead than retrospective reporting.
- Employ explainable predictive models to ensuring that operational team can understand and act upon the driver of predicted cancelation and returns.

6.2.3 Recommendations for Researchers and Analytics

- Researchers work on data-poor markets are encouraged to adopting theoretically grounded synthetics data generation, expanding variables to including more influential aspects as product specifications, provided that validation and consistency processes is transparently implemented.
- Greater emphasis should be placed on interpretable predictive modeling to enhancing the interpretability and practical relevance of analytics-based consumers behavior research findings.

- Emphasis should be placed on model interpretability and transparency to ensuring that predictive insights can be effectively translated to operation actions.
- On data-scarce environment, analytics team should adopts flexible, simulation-based approaches to modeling development while maintaining rigorous validation and governance standards.

6.3 Limitations of the Study

- This study rely on synthetically generated transactional data instead than real-world e-commerce datasets, that limit the ability to claiming direct empirical generalization despite the apply theoretical grounding and validation procedures.
- The synthetic dataset reflects operation and behavioral rules that derived from prior literature, expert-informed constraints and some online retailers' information; thus, unobserved real-world behavioral nuance may not be fully captured.
- The analysis is confined for order-level transactional and operational variables and don't incorporate granular behavioral data as clickstream activity, brows duration, or customers feedback, which may further enrich predictive performance.
- Predictive models were evaluated in a controlled simulation environment, and external validation by using real transactional data from Palestinian e-commerce platforms weren't feasible cause of data accessibility and confidentiality constraints.
- The study focus on interpretable and computationally efficient classification models; more complex modeling approaches (e.g., deep learning architectures) wasn't explored, which may limit performance optimization but preserves analytical transparency.

6.4 Directions for Future Research

- Future studies should validate the proposed analytical frameworks by using real transactional data from e-commerce platforms when access become available, in due to assessing external validity and generalizability.
- Longitudinal datasets spanning longer time horizon should be employed to examining how cancelation and return behavior evolve over repeat purchase cycles and change operational conditions.

- Integrate behavioral data sources, as clickstream activity, customer review and post-purchase feedback, may enhancing the predictive power and behavior depth of future models.
- Comparative research across emerging markets with similar logistical, institutional, and payment constraints would providing valuable insights to the transferability of business intelligence–driven predictive models.
- More research should investigate how predictive insights can be embedded to real-time decision-support systems, enable dynamic intervention during order process and fulfillment stages.
- Future research may apply more advanced predictive technique, like gradient boosting models (e.g., XGBoost), to evaluating whether higher predictive accuracy could be achieved when maintaining practical applicability on e-commerce decision-support systems.

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Appendices

Appendix (A)

Simulation Assumptions

Assumption Category	Description of the Assumption	Purpose / Methodological Justification
Nature of Data	All records represent historical e-commerce transactions that have already reached a final outcome (Completed, Cancelled, or Returned).	Ensures ex-post analysis validity and avoids ambiguity in outcome interpretation in predictive modeling.
Study Timeframe	Order dates are distributed between January 1, 2023 and December 31, 2025.	Captures temporal variability and seasonality effects relevant to e-commerce behavior analysis.
Order Outcome Structure	Order status is a three-class target variable: completed, cancelled, or returned.	Supports multi-class classification tasks in supervised machine learning models.
Cancellation Logic	Order cancellations occur only before shipment or delivery; cancelled orders have no delivery date.	Maintains operational and temporal consistency with real-world e-commerce fulfillment processes.
Return Logic	Returns occur only after successful delivery and are associated with a documented return reason.	Preserves causal validity between delivery completion and return behavior.
Delivery Time (Regular Periods)	Delivery duration ranges between 3 and 5 days for non-peak periods.	Reflects standard last-mile delivery performance in typical e-commerce operations.
Delivery Time (Black Friday Period)	Delivery duration may extend up to 14 days during Black Friday due to operational congestion.	Models peak-season logistics pressure and its behavioral consequences.
Return Trigger – Slow Delivery	"Slow delivery" is considered a valid return reason, particularly after the Black Friday period.	Aligns with documented negative effects of delivery delays on customer satisfaction and retention.
Product Pricing	Product prices are constrained between 10 and 500 ILS.	Prevents unrealistic price outliers and maintains economic plausibility in the simulated data.
Order Quantity	Single-item orders account for approximately 90% of transactions; multi-item orders occur less frequently.	Reflects dominant consumer purchasing patterns in online retail environments.

Assumption Category	Description of the Assumption	Purpose / Methodological Justification
Discount Policy	Discounts are applied only to frequent customers, large quantities (5%), or during Black Friday promotions (10%).	Simulates realistic promotional strategies used in e-commerce platforms.
Discount Effect on Outcomes	When a discount is applied, the probability of cancellation or return drops below 5%.	Incorporates empirically supported behavioral effects of price incentives.
Payment Methods	Four payment methods are used with predefined proportions (COD, bank card, wallet, PayPal).	Ensures realistic distribution of payment preferences observed in the local market context.
Customer Gender	Customer gender distribution is fixed at 69% female and 31% male.	Reflects observed demographic patterns in online shopping behavior.
Customer Type (Conceptual)	Customers are categorized as regular or frequent, with frequent customers exhibiting near-zero cancellation rates.	Introduces customer heterogeneity critical for predictive modeling performance.

Appendix (B)

Tables

Table 1

Data Schema

Variable (Description)	Column Name	Variable Role	Data Type	Values / Range	Consistency Notes
Order ID	order_id	Identifier	Integer/ String	Unique per order	Primary key
Product ID	product_id	Identifier	Integer/ String	—	May repeat across orders
Customer ID	customer_id	Identifier	Integer/ String	—	Identifies the customer
Customer Type	customer_type	Independent (Derived)	Categorical	Frequent, Regular	Derived using order frequency (Q75)
Customer Gender	customer_gender	Independent	Categorical	Female (69%), Male (31%)	Fixed distribution
Product Category	category	Independent	Categorical	Fashion, Electronics, Home, Toys, Sports, Beauty, Grocery	Distribution derived from external dataset
Order Date	order_date	Independent	Date	—	Used to identify Black Friday period
Season	season	Independent (Derived)	Categorical	Spring, Summer, Autumn, Winter	Derived from order_date
Delivery Date	delivered_date	Independent	Date/ NULL	—	NULL if order is cancelled
Order Status (Target)	order_status	Dependent (Target)	Categorical	Returned (30%), Cancelled (8%), Completed (62%)	Subject to business rules
Return Reason	return_reason	Descriptive / Exploratory	Categorical / NULL	Defective, Not as described, No longer needed, Missing/Wrong item, Slow delivery	Filled only if order is returned
Quantity	quantity	Independent	Integer	1 (90%), 2–3 (10%)	Mainly individual purchases
Unit Price	price	Independent	Numeric	10–500 ILS (excluding furniture)	Furniture handled separately if included
Payment Method	payment_method	Independent	Categorical	COD 75%, Card 15%, Wallet 6%, PayPal 4%	Fixed market-based distribution
Discount Rate	discount_rate	Independent	Numeric	0, 0.05, 0.10	Conditional rules apply

Variable (Description)	Column Name	Variable Role	Data Type	Values / Range	Consistency Notes
Delivery Lead Time	delivery_lead_time_days	Independent	Integer	3–5 normally, 3–14 during Black Friday	Derived variable
Order Value	order_value	Independent	Numeric	price × quantity × (1 − discount_rate)	Derived variable for analysis

Appendix (C)

Figures

Figure 11

Customer Type Distribution Across Order Status

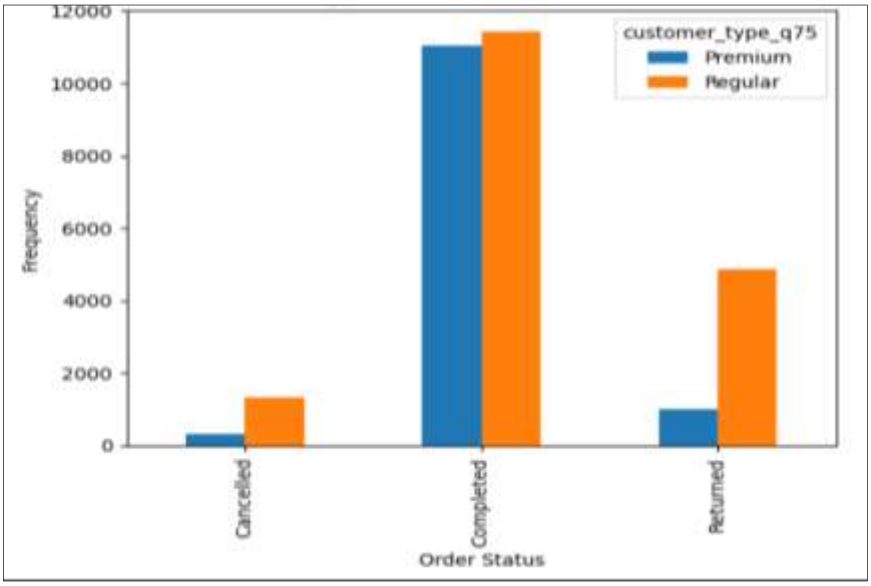


Figure 12

ROC curves

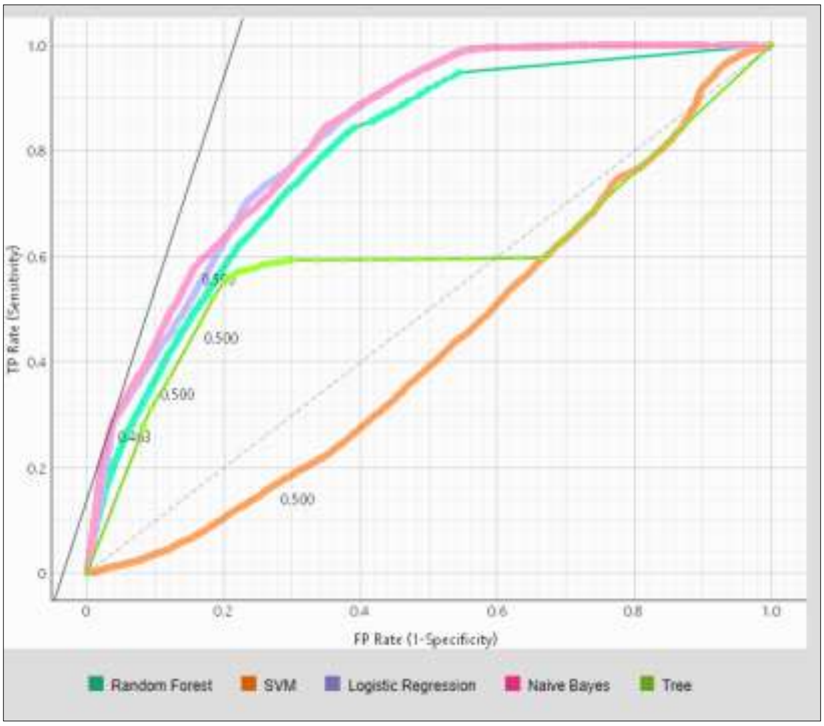


Figure 13

Confusion Matrix for the Random Forest

Actual \ Predicted	Cancelled	Completed	Returned	Σ
Cancelled	951	270	429	1650
Completed	1530	16912	4032	22474
Returned	666	1577	3633	5876
Σ	3147	18759	8094	30000

Figure 14

Confusion Matrix for the Naive Bayes

Actual \ Predicted	Cancelled	Completed	Returned	Σ
Cancelled	1561	85	4	1650
Completed	0	20018	2456	22474
Returned	0	3683	2193	5876
Σ	1561	23786	4653	30000

Figure 15

Random Forest Feature Importance

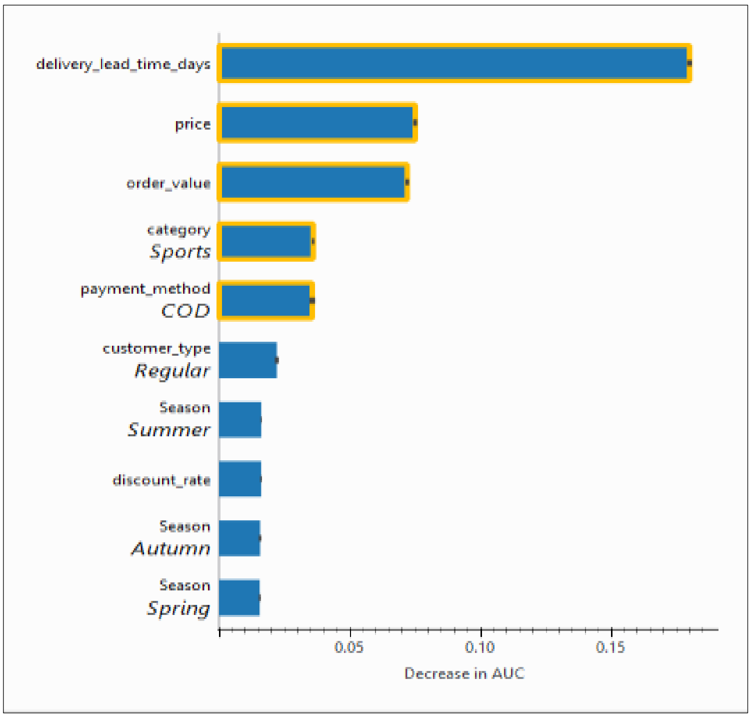


Figure 16

Naïve Bayes Feature Importance

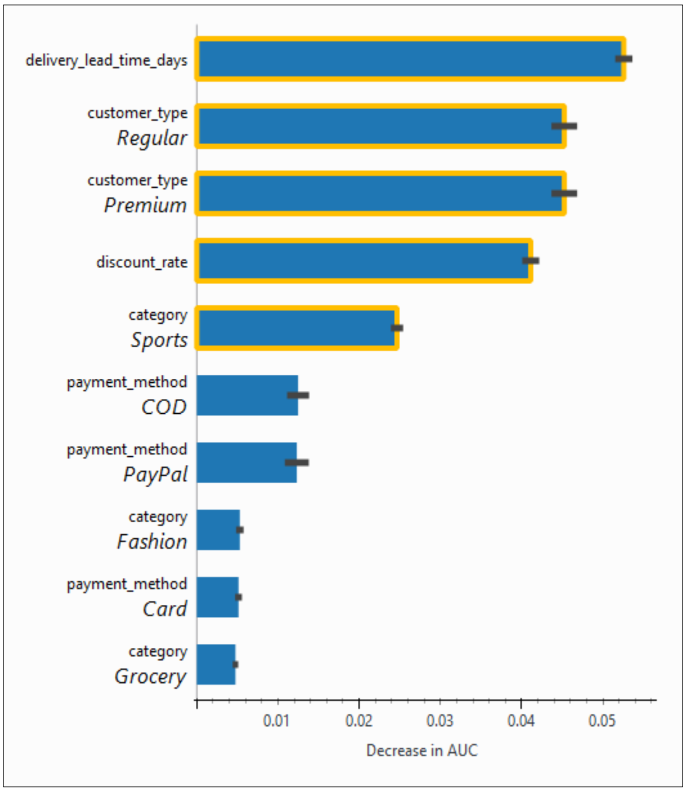


Figure 17

Explain Random Forest Results

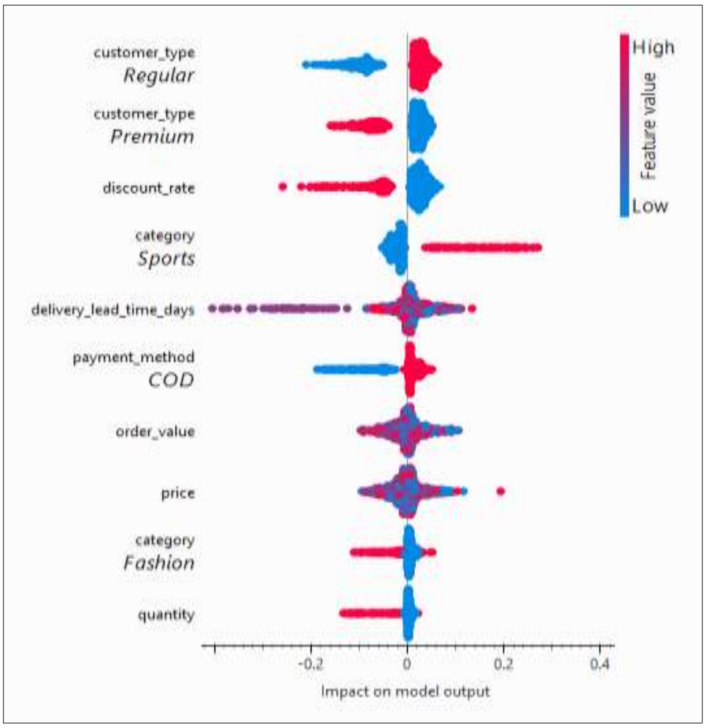


Figure 18

Explain Naïve Bayes Results

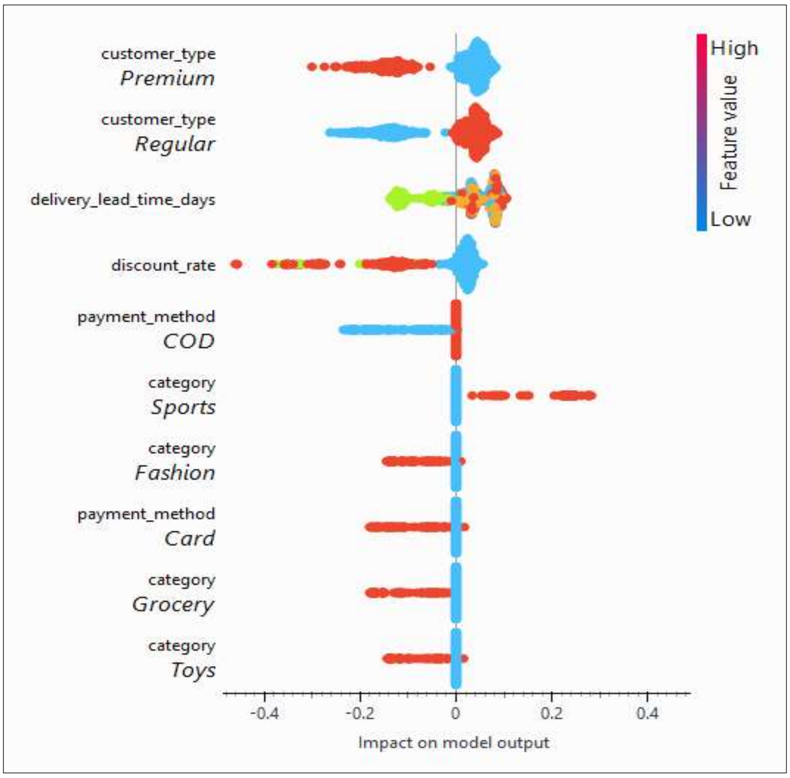
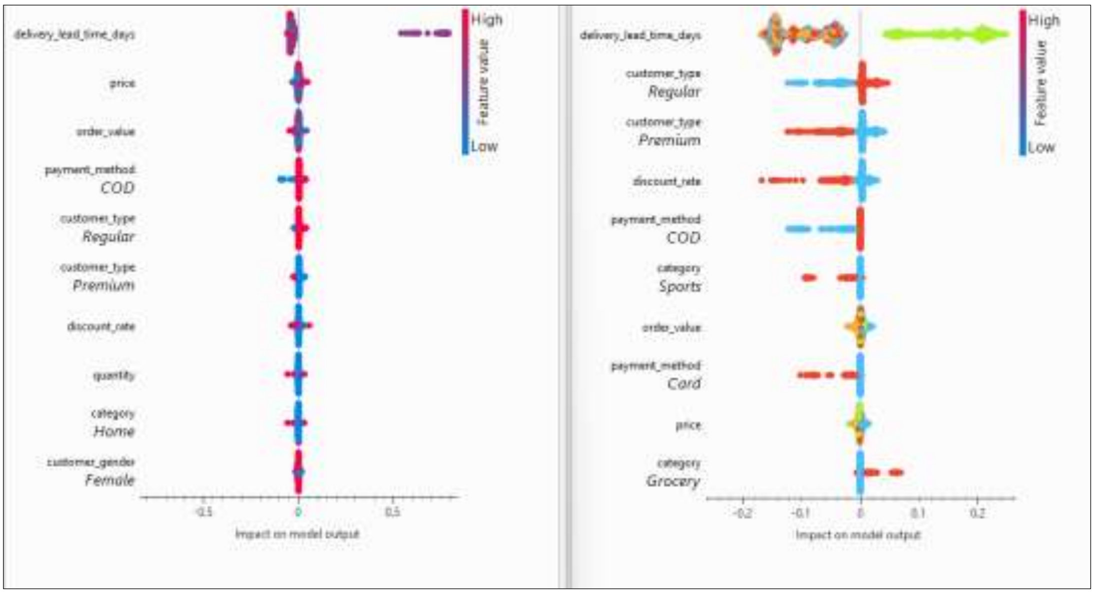


Figure 19

Comparative Models Explainability Analysis for Cancelled Orders



جامعة النجاح الوطنية
كلية الدراسات العليا

إطار قائم على ذكاء الأعمال لتحليل سلوك المستهلك عبر الإنترنت: تطبيق قائم على المحاكاة في سياق السوق الفلسطيني

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قدمت هذه الرسالة استكمالاً لمتطلبات الحصول على درجه الماجستير في برنامج ذكاء الاعمال وتحليل البيانات، من كلية الدراسات العليا، في جامعة النجاح الوطنية، نابلس– فلسطين.

2026

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الملخص

قامت الدراسة بفحص التجارة الإلكترونية في فلسطين لفهم سلوك المستهلكين عبر الإنترنت بعد الشراء، من خلال تحليل حالات إلغاء الطلبات وإرجاع المنتجات ضمن إطار تحليلي قائم على ذكاء الأعمال. وقد طوّر البحث مجموعة بيانات اصطناعية تعتمد على قواعد نظرية لمحاكاة العمليات التجارية المحلية، وذلك نتيجة الرغبة في إنشاء قاعدة بيانات تمثل سجلات معاملات فعلية، مع عدم توفر إمكانية الوصول إلى بيانات معاملات حقيقية. استخدمت الدراسة التحليل الوصفي التشخيصي إلى جانب نماذج تعلم الآلة الخاضعة للإشراف للتنبؤ بنتائج الطلبات وتحديد عوامل المخاطر الرئيسية. وأظهرت النتائج أن مدة التوصيل تُعد العامل الأكثر تأثيرًا في كلٍ من إلغاء الطلبات وإرجاع المنتجات، تليها طريقة الدفع وقيمة الطلب وسلوك الشراء لدى العميل كعوامل ثانوية. وقدمت النماذج التجميعية والاحتمالية نتائج موثوقة وسهلة التفسير، مما يجعلها مناسبة لدعم اتخاذ القرار في الأسواق التي تعاني من محدودية البيانات. وتُظهر الدراسة أن البيانات الاصطناعية التي خضعت للتحقق التحليلي، عند دمجها مع ذكاء الأعمال والتحليلات التنبؤية، يمكن أن تولّد رؤى عملية تساعد شركات التجارة الإلكترونية على إدارة عملياتها ومخاطر ما بعد الشراء في الدول النامية.

الكلمات المفتاحية: ذكاء الأعمال، البيانات الاصطناعية، البيانات المُحاكاة، سلوك المستهلك عبر الإنترنت، التجارة الإلكترونية، تعلم الآلة، سلوك ما بعد الشراء، التنبؤ بإرجاع الطلبات، السوق الفلسطيني.