International Journal for Multidisciplinary Research (IJFMR)
E-ISSN: 2582-2160 ● Website: www.ijfmr.com ● Email: editor@ijfmr.com

A Study on Gen Z-Focused Customer-Centric Risk Assessment Model to Predict Delivery Delays in E-Commerce Supply Chains

Fathima Saniya P P[1], Ms. Honey Poothullil Johnson[2]

[1]MBA Student, SCMS School of Technology and Management, Aluva, Cochin, Kerala – 683106.
[2]Assistant Professor, Department of Business Administration, SCMS School of Technology and Management, Aluva, Cochin, Kerala – 683106.

Abstract
This study focuses on the problem of delivery delays in e-commerce and how they influence customer satisfaction, especially among Gen Z consumers. With the rapid growth of online shopping, customers now expect faster and more reliable delivery services. When these expectations are not met, it often leads to dissatisfaction, reduced trust, and customers choosing alternative platforms. This study aims to understand the reasons behind delivery delays and explore ways to reduce them effectively.
The research is based on data collected from 261 respondents using a structured questionnaire. It examines three important areas, namely operational factors, AI-based technology monitoring, and service measures. The data was analysed using statistical tools in Jamovi along with machine learning models developed through the Orange Data Mining tool. Techniques such as descriptive statistics, reliability analysis, correlation, logistic regression, and independent samples t-test were used to understand the relationships between variables, while machine learning methods like Random Forest and Gradient Boosting were applied to improve prediction of delivery delays.
The findings indicate that delivery delays are quite common, with more than half of the respondents experiencing delays in their most recent orders. Among the factors studied, operational issues such as inefficient inventory management, slow order processing, and challenges in last-mile delivery were found to be the most significant causes of delays. Technology-based monitoring showed a positive but limited impact on its own, suggesting that it becomes more effective when combined with strong operational systems. Service measures also played a role, as customers with higher expectations were more sensitive to delays. The study also shows that machine learning models can help in predicting delivery delays in advance. Even though the accuracy of these models is moderate, they are capable of identifying high-risk orders, allowing businesses to take preventive actions instead of reacting later.

Keywords: Delivery Delay, E-Commerce, Gen Z, Supply Chain, Machine Learning, Random Forest, Logistic Regression, Customer Satisfaction

1. Introduction

When deliveries are late, the impact on a business can be felt in many ways. The most immediate problem is the extra costs that pile up. Companies end up paying for additional warehousing, inventory storage,

and in some cases, fines and penalties for missing deadlines set in contracts. These unplanned expenses quietly eat into profits over time.
The damage does not stop there. A single delayed shipment can throw the entire supply chain out of sync. When goods do not arrive on time, production slows down, efficiency drops, and essential items can run out completely. Businesses then find themselves struggling to fulfil customer orders while also trying to keep their day-to-day operations running smoothly.
Customer trust is also at stake. People notice when their orders arrive late especially Gen Z and they are not shy about expressing their disappointment. Negative reviews, complaints, and word of mouth can spread quickly, and a business that consistently fails to deliver on time soon finds its reputation taking a serious hit.
Gen Z consumers are a demanding, digitally native audience. They expect fast, reliable, and transparent delivery as a basic standard not a premium feature. When their expectations are not met, they notice it more acutely than older consumer groups, and the data confirms this heightened sensitivity.
Inside the organization, delays push teams into constant problem-solving mode. Schedules are rearranged, production plans are rewritten, and urgent orders become a regular occurrence. Over time, this kind of reactive work exhausts employees, stretches resources, and brings down overall productivity.
What often goes unnoticed is how delays quietly damage business relationships. Suppliers, partners, and stakeholders all rely on consistency and dependability. When that breaks down repeatedly, trust fades, partnerships become difficult, and in serious cases, contracts are lost altogether.
In the business environment where the e-commerce scene has largely gained momentum with the rise of digital retail, the expectations of customers in relation to service reliability and other factors have remarkably risen. In the past where traditional supply chain models have become the dominant force in the management of organizational supply chains, focusing on issues of internal efficiencies and cost minimization via forecast-based strategies have become inadequate in serving the expectations of the customer. In this regard, organizations have adopted the customer-centric supply chain model where decision-making and strategies of the entire supply chain process are concerned with providing customer satisfaction.
Approximately 58% of e-commerce shoppers abandon retailers after a poor delivery experience, with 79% not returning after receiving late deliveries, indicating that supply chain issues are a major driver of customer churn. Poor logistics, including slow shipping and lack of tracking, contribute heavily to the overall e-commerce churn, which often ranges from 60-80% annually. This research develops an innovative model leveraging AI to incorporate these elements for proactive delay prediction.

1.1 Background of the Study

Online shopping has grown enormously over the past decade. More people than ever are buying things on the internet, and that has changed the way businesses work and the way customers think. One of the biggest changes is how people now feel about delivery. Not too long ago, waiting a week or two for an order to arrive was perfectly normal. Today, many customers especially Gen Z expect their packages to show up the next day, or even the same day. Companies like Amazon have made this kind of fast delivery feel like the standard, and other businesses are now under pressure to keep up. If a business cannot deliver on time, customers will simply go somewhere else.
For a long time, businesses managed their supply chains using methods that were mainly focused on cutting costs and working efficiently on the inside. These older approaches worked well enough when things were predictable, but online shopping has made everything more complicated. Demand can change

very quickly, suppliers are spread across the world, and customers are far less patient than they used to be. The old ways of planning and forecasting simply were not built for this kind of environment.

This is where Machine Learning comes in. Machine Learning is a type of artificial intelligence that learns from data. Instead of following fixed rules, it looks at large amounts of past information and finds patterns that humans might miss. When applied to delivery management, it can look at things like order histories, stock levels, seasonal trends, and transport routes to figure out which orders are likely to arrive late. What makes this especially useful is that it can raise an early warning before the delay actually happens, giving businesses a chance to act before the customer is affected.

1.2 Statement of the Problem

Delivery delays are a critical issue in e-commerce supply chains, affecting customer satisfaction and business performance. Traditional methods fail to predict delays effectively due to complex and dynamic risk factors. Hence, there is a need for a Machine Learning based, customer-centric model to accurately predict delivery delays and support proactive decision-making.

1.3 Relevance and Scope of the Study

This study examines delivery risks from the customer's viewpoint, including expectations on delivery speed, service reliability, and satisfaction levels related to delayed shipments. Along with analysing how operational elements like demand forecasting, inventory positioning, and logistics optimization influence delivery timelines. This study examines Machine Learning because it helps to identify hidden patterns and improves prediction accuracy.

1.4 Objectives of the Study

- To develop a predictive model using Logistic Regression as the primary analytical technique, supported by machine learning algorithms such as Gradient Boosting and Random Forest, to forecast the probability of delivery delays in e-commerce supply chains.
- To examine how technology can be used to monitor and mitigate delay risks.
- To recommend operational measures for e-commerce firms to reduce delivery delays and enhance service efficiency.

2. Review of Literature

The SERVQUAL Model and the Supply Chain Risk Management (SCRM) Theory serve as the foundation for this study. These two theories were selected because they complement each other well in addressing the primary issue of this study, which is the delivery delays that Gen Z consumers encounter in e-commerce supply chains. The operational side of why delays occur and how they can be anticipated and managed are explained by SCRM. Conversely, SERVQUAL incorporates the viewpoint of the customer by documenting how Gen Z consumers perceive and evaluate delays. When taken as a whole, they offer this study a solid and useful theoretical foundation.

Zsidisin and Ritchie (2008) introduced the theory of supply chain risk management. This theory focuses on locating, assessing, and mitigating risks that could impede the efficient flow of products and services through a supply chain. One of the most prevalent and obvious types of supply chain risk in the context of e-commerce is delivery delay.

In 1988, Parasuraman, Zeithaml, and Berry created the SERVQUAL Model. This model defines service quality as the difference between what a customer expects from a service and what they actually receive. The RATER framework, which stands for Reliability, Assurance, Tangibles, Empathy, and

Responsiveness, is a set of five dimensions used to measure this gap. In the context of e-commerce delivery, each of these dimensions has significance.

2.1 An Overview of Earlier Studies

Tang et al. (2024) develop an IoT-based Cold-Chain Logistics Service Quality (ICCLSQ) model to examine how digital technologies influence logistics service quality in fresh product e-commerce. Using Structural Equation Modelling (SEM) and survey data from 522 respondents, the research identifies key service dimensions such as customer satisfaction, privacy, security, and return intentions.

Islam et al. (2025) propose an explainable machine learning framework to predict delivery delays and supply chain risks in smart logistics systems. The study uses the DataCo SMART dataset with more than 182,000 records and applies various statistical and machine learning techniques such as Linear Regression, Ridge Regression, Random Forest, and Gradient Boosting.

Hudnurkar et al. (2024) examine the application of artificial intelligence and machine learning techniques in predicting delays in truck delivery logistics. The study employs multiple algorithms, including Artificial Neural Networks, Decision Trees, Random Forest, Support Vector Machines, and AdaBoost classifiers.

Mirzaei et al. (2025) highlight the growing dominance of machine learning approaches in predicting delivery delays across supply chains. The study compares multiple algorithms and shows that hybrid and optimized models outperform traditional statistical methods. Despite these advancements, most studies fail to incorporate customer-centric variables such as behavioral patterns and expectations.

Rezki and Mansouri (2024) present a machine learning-based framework to predict delivery delays and evaluate supplier performance. The study applies multiple algorithms, including Random Forest, Gradient Boosting, and Logistic Regression. Ensemble models demonstrate superior performance compared to individual models.

Wani et al. (2022) propose a Hybrid Late Delivery Algorithm (HLDA) to predict shipment delays in e-commerce supply chains. The study combines multiple machine learning models into a unified framework. The final model uses a weighted voting mechanism, which enhances prediction accuracy compared to individual models.

Kandula et al. (2021) propose a two-stage prescriptive analytics framework that combines machine learning with routing optimization. The first stage uses XGBoost to predict delivery success probabilities. The second stage applies Vehicle Routing Problem with Time Windows (VRPTW) optimization to improve delivery scheduling.

2.2 Uniqueness of Research Study

Unlike many traditional studies that mainly focus only on logistics efficiency, this study takes a broader and more practical approach. It combines three important aspects: operational factors, AI-based technology monitoring, and service measures into one single framework. This helps in understanding delivery delays not just from the company's internal processes, but also from the role of technology and customer experience.

Another important strength of this research is its focus on Gen Z consumers. This group represents one of the most active online shopping segments today. They are used to fast services, real-time updates, and smooth delivery experiences. Compared to general studies that include all age groups, this focused approach makes the findings more meaningful and useful for modern e-commerce businesses.

The study is also unique because it uses both statistical methods and machine learning techniques. Traditional methods like logistic regression help in understanding clear relationships between variables, while machine learning models like Random Forest and Gradient Boosting help capture more complex and hidden patterns in the data. By using both approaches together, the study is able to analyse delivery delays in a deeper and more accurate way.

3. Methodology

3.1 Research Approach and Design

The type of research design used in the research study is descriptive quantitative research design, based on observable facts and measurable data. Quantitative research design is appropriate for determining the cause-and-effect relationship between independent variables such as operational factors, AI technology in logistics, and service measures, and the dependent variable, which is risk of delivery delay.

3.2 Sources of Data

For the purpose of this study, primary data has been collected through a structured questionnaire survey conducted among Gen Z consumers, who are in the range of 16-28 years of age and have ordered products from online platforms within a certain period of time. The questionnaire survey has been conducted online through Google Forms. Secondary data has been collected from various sources such as journal articles, industry reports from organizations and government databases related to the topic of e-commerce logistics in India.

3.3 Sampling Design

Convenience sampling was used as a method for selecting the respondents for the study. The target population for the study is the Gen Z consumers who fall in the age group from 16 to 28 years, purchasing products through the electronic commerce websites Amazon, Flipkart, Meesho, etc. The sample size for the study is around 261 consumers to make the study more reliable.

3.4 Data Analysis Tools

This study used a set of carefully selected tools to collect, organise, and analyse the survey data. Google Forms was used to design and distribute the survey questionnaire to Gen Z online shoppers. Microsoft Excel was used to organise and do an initial review of the raw data. Jamovi was the primary tool used for data analysis in this study, used to perform descriptive statistics, frequency analysis, and to examine the relationships between the survey variables. The Orange Data Mining tool was used to apply advanced machine learning algorithms like Random Forest and Gradient Boosting.

3.5 Limitations of the Study

The first limitation is the sample size. This study collected 261 responses, which is relatively small when compared to the full size of the Gen Z shopping population. The second limitation is that the data is entirely based on customer perceptions rather than actual logistics records. The third limitation relates to the geographic scope of the study, where most respondents were from urban and semi-urban areas in India. The fourth limitation is that this study focused exclusively on Gen Z respondents, meaning the results cannot be generalised to other age groups.

4. Data Analysis, Interpretation and Inference

4.1 Demographic Analysis

4.1.1 Age Distribution

Table 1: The Profile of Respondents Based on Age

Age	Count	Percentage
16 – 18	8	3.07%

19 – 21	27	10.34%
22 – 25	139	53.26%
26 – 28	87	33.33%

Interpretation:

The respondents in this study are mainly young adults. More than half, specifically 53.26%, are between 22 and 25 years old, making this the largest group by a significant margin. This is expected for research focused on e-commerce delivery experiences, as this age group represents the main digital native generation that shops online the most and has high expectations for delivery speed and reliability. The second largest group includes those aged 26 to 28, making up 33.33% of respondents. Together, these two groups account for nearly 87% of all respondents.

Inference:

These are people who grew up with smartphones in hand, who treat next-day delivery not as a luxury but as a basic expectation, and who are most likely to abandon a platform entirely after even a single poor delivery experience. For the purposes of this research, that focus is precisely where the most relevant and actionable insights about delivery delay perceptions are likely to be found.

4.1.2 Gender Distribution

Table 2: The Profile of Respondents Based on Gender

Gender	Count	Percentage
Female	147	56.32%
Male	114	43.68%

Interpretation:

From the data, it can be seen that the female respondent distribution makes up 56.32%, whereas the male respondent distribution represents 43.68%. The gender-based distribution is quite even, and hence both genders are taken into account in the study.

Inference:

The presence of both male and female respondents in considerable proportions enhances the reliability and validity of the study. Since Gen Z consumers are highly active in online shopping, this distribution helps in capturing diverse opinions regarding delivery delays and service quality.

4.1.3 Occupation

Table 3: The Profile of Respondents Based on Occupation

Occupation	Count	Percentage
Employed	81	31.64%
Self-employed	50	19.53%
Student	125	48.83%

Interpretation:

It can be seen from the table that 48.83% of the total respondents are students. They constitute the largest segment among the study respondents. The next largest segment includes the employed respondents who are 31.64%, while the self-employed respondents constitute 19.53%.

Inference:

The higher percentage of students implies that the research findings are more inclined towards the perception of online purchasing behavior of younger people who are active online buyers. Students generally have high expectations in terms of prompt deliveries and regular updates, which means that service quality is of utmost importance for them.

4.1.4 Frequency of Online Shopping

Table 4: The Profile of Respondents Based on Frequency of Online Shopping

Frequency of Online Shopping	Count	Percentage
Monthly	84	32.18%
Occasionally	157	60.15%
Weekly	20	7.66%

Interpretation:

From the table presented above, it can be seen that the number of individuals involved in occasional online shopping is the highest with a percentage of 60.15%. Monthly online shoppers account for 32.18%, whereas those who shop weekly have a very low percentage of 7.66%.

Inference:

The prevalence of occasional buyers implies that the majority of participants rely on e-commerce websites according to their needs rather than out of routine behavior. Such consumers can expect moderate shipping times, yet still require punctuality while placing orders.

4.1.5 Preferred E-Commerce Platform

Table 5: The Profile of Respondents Based on Preferred E-Commerce Platform

Preferred E-Commerce Platform	Count	Percentage
Amazon	143	56.75%
Flipkart	87	34.52%
Meesho	22	8.73%

Interpretation:

It has been seen that 56.75% of respondents favor Amazon as the best option for e-commerce activities, followed by 34.52% preferring Flipkart and 8.73% Meesho. From this analysis, it can be interpreted that the majority of respondents choose e-commerce platforms with a known reputation.

Inference:

The high percentage preference for Amazon can be attributed to the fact that consumers feel more comfortable when they are provided with a regular pattern of experience. Therefore, reputation plays an important role in selecting e-commerce platforms. The relatively higher percentage of preference for Flipkart indicates it as a competitive brand in the market. Meanwhile, Meesho gets the lowest preference amongst these three brands.

4.1.6 Delivery Location

Table 6: The Profile of Respondents Based on Delivery Location

Delivery Location	Count	Percentage
Rural	31	11.88%
Semi-Urban	125	47.89%
Urban	105	40.23%

Interpretation:

From the above table, it can be seen that the largest proportion of respondents, which is 47.89%, comes from semi-urban areas. On the other hand, 40.23% of the respondents are from urban areas, whereas the lowest number of respondents, which is 11.88%, come from rural areas.

Inference:

It is found that the highest number of respondents belongs to semi-urban areas, and it depicts the fast growth of e-commerce usage even beyond cities. A significant percentage of the respondents from urban areas implies high adoption of e-commerce platforms among city people.

4.1.7 Preferred Payment Mode

Table 7: The Profile of Respondents Based on Preferred Payment Mode

Preferred Payment Mode	Count	Percentage
Card	18	6.90%
Cash on Delivery	70	26.82%
Net Banking	3	1.15%
UPI	170	65.13%

Interpretation:

As it is evident from the data, 65.13% of the respondents prefer UPI as their payment mode. This is followed by 26.82% respondents preferring Cash on Delivery mode. 6.90% respond that they pay through cards and only 1.15% respondents have mentioned that they pay through net banking.

Inference:

High preference of UPI by the customers implies that customers find it easy, fast, and convenient for them. It indicates that there has been a trend for digital payments by the respondents. Significant proportion of customers using cash-on-delivery as their payment mode implies that they have the tendency to receive the product first before making the payment.

4.1.8 Delayed Delivery

Table 8: The Profile of Respondents Based on Delayed Delivery

Delayed Delivery	Count	Percentage
No	125	47.89%
Yes	136	52.11%

Interpretation:
The above-mentioned table reveals whether the respondents have faced a delay in the latest order placed by them. It can be seen that 52.11% of the respondents have been facing delays while placing orders online whereas 47.89% have not experienced any kind of delay in delivery.
Inference:
The high percentage of respondents having experienced delay in the latest order placed by them signifies that delays are quite prevalent among customers when using online shopping facilities. As such it may be said that delays are one of the major problems for which the customers have to be concerned when opting for e-commerce services.

4.2 Reliability Analysis (Cronbach's Alpha)
Reliability analysis is an important method used to ensure that the consistency and dependability of the measurement tool are measured. To evaluate the reliability of the questionnaire, Cronbach's Alpha was used. The general rule is that a Cronbach's alpha score of 0.70 and higher should be considered as the lower boundary for acceptable levels of reliability in social sciences.

Table 9: Reliability Analysis (Cronbach's Alpha)

Objectives	Cronbach's Alpha	Interpretation
Operational Factors	0.792	Acceptable
AI-Based Technology Monitoring	0.902	Excellent
Service Measures	0.898	Good to Excellent

Based on the reliability test carried out in Jamovi, it is evident that all the three measuring scales adopted in this research are reliable. The Cronbach's alpha value for Operational Factors is 0.792, which is quite acceptable, whereas for AI-Based Technology Monitoring and Service Measures, the values are 0.902 and 0.898, respectively. All the three values exceed the threshold value of 0.70 and are therefore reliable for the purposes of conducting research. This conclusion validates that the questionnaire is appropriate and suitable for predictive modeling and logistic regression analysis.

4.3 Correlation Matrix

Table 10: Correlation Matrix

	Operational Factors	AI-Based Technology Monitoring	Service Measures
Operational Factors	—		
AI-Based Technology Monitoring	Pearson's r = 0.503*** p < .001	—	
Service Measures	Pearson's r = 0.637*** p < .001	Pearson's r = 0.737*** p < .001	—

Interpretation:
There is a medium level of correlation between operational factors and AI-based technology monitoring

(r = 0.503). It means that the higher the level of efficiency, the more likely that an organization is going to use new technologies for monitoring purposes. The relationship between operational factors and service measures is strong (r = 0.637). There is a very strong connection between AI-based technology monitoring and service measures (r = 0.737), confirming that the implementation of new technologies affects service measures positively. The p-value of all correlations is less than 0.001, providing 99.9% confidence in the relationships.

4.4 Descriptive Analysis

Table 11: Descriptive Analysis

Statistic	Operational Factors	AI-Based Technology Monitoring	Service Measures
N	261	261	261
Missing	0	0	0
Mean	2.05	1.90	1.94
Median	2.00	2.00	2.00
Standard Deviation	0.505	0.517	0.563
Minimum	1.00	1.00	1.00
Maximum	3.20	4.29	4.25

Interpretation:

This descriptive analysis describes the central tendency and dispersion of the key variables. The number of observations in each variable equals 261 without any missing values. The mean values of operational factors, AI-based technology monitoring, and service measures (2.05, 1.90, and 1.94, correspondingly) are quite close to one another, which means that respondents rated all three dimensions moderately well. Standard deviation values are relatively low (between 0.505 and 0.563), meaning that there is not much variance among the responses. The slightly higher maximum values in relation to AI monitoring and services suggest that there is still room for improving the performance in those fields.

4.5 Regression Analysis

Binomial Logistic Regression (Analysis done with Jamovi 2.6.26):

Table 12: Model Fit Measures

Model	Deviance	AIC	R^2McF	R^2N	χ^2	df	p
1	347	355	0.0411	0.0737	14.8	3	0.002

Table 13: Model Coefficients

Predictor	Estimate	SE	Z	p	Odds Ratio
Intercept	1.874	0.603	3.11	0.002	6.515

Operational Factors	-1.127	0.343	-3.29	0.001	0.324
AI-Based Technology Monitoring	-0.493	0.366	-1.35	0.178	0.611
Service Measures	0.755	0.382	1.97	0.048	2.127

Table 14: Prediction (Classification Table)

Observed	Predicted: 0	Predicted: 1	% Correct
0	66	59	52.8%
1	46	90	66.2%
Accuracy		0.598	AUC: 0.641

4.5.1 Objective 1: Predictive Model Using Logistic Regression

Hypothesis H1: Operational factors in e-commerce logistics significantly influence (reduce) the occurrence of delivery delays.

Interpretation:

The binomial logistic regression model is statistically significant ($\chi^2 = 14.8$, $p = 0.002$), indicating that the predictors collectively explain delivery delay occurrence. Among the predictors, Operational Factors have a significant negative effect ($\beta = -1.127$, $p = 0.001$, OR = 0.324). This implies that improvements in operational efficiency, such as faster order processing, better inventory management, and efficient last-mile delivery will significantly reduce the likelihood of delivery delays. The model's prediction accuracy is 59.8% with AUC = 0.641, indicating moderate classification performance.

Inference:

The predictive model is statistically valid but moderately strong, with operational factors emerging as the most critical determinants of delivery delay risk. Enhancing logistics efficiency can significantly reduce delays in e-commerce supply chains. H1 is accepted.

4.5.2 Objective 2: Technology Monitoring and Delay Mitigation

Hypothesis H2: Technology-driven monitoring systems significantly reduce the perceived risk and occurrence of delivery delays.

Interpretation:

The analysis yielded a p-value of 0.178 for AI-Based Technology Monitoring. Since this is greater than the significance threshold of 0.05, the variable is not a statistically significant predictor in this specific model. While not significant, the direction of the effect is negative (Estimate = −0.493), suggesting that as technology monitoring increases, the likelihood of a delay tends to decrease. This indicates an Execution Gap: while technology can successfully monitor a shipment, its ability to mitigate a delay is secondary to core operational efficiencies.

Table 15: Independent Samples T-Test

Test	Statistic	df	p
AI-Based Technology Monitoring (Student's t)	1.76	259	0.080

Inference:

The analysis suggests that while technology is a critical component of modern logistics, it does not currently serve as a primary independent mitigator of delivery delays. Technology should be viewed as a supportive transparency tool rather than a standalone solution. H2 is not supported at the 0.05 significance level.

4.5.3 Objective 3: Service Measures and Operational Recommendations

Hypothesis H3: Service measures significantly influence delivery delays and improve service efficiency.

Interpretation:

The logistic regression results indicate that Service Measures have a positive and statistically significant effect on delivery delay ($\beta = 0.755$, $p = 0.048$, OR = 2.127). This positive correlation shows that attributes of services such as communication, flexibility of delivery, customer service, and handling complaints are positively correlated to the results of delayed deliveries. The odds ratio (2.127) further suggests that an increase in service-related factors more than doubles the likelihood of delivery delays.

Inference:

Since the p-value (0.048) is less than 0.05, H3 is accepted, indicating that service measures have a statistically significant impact on delivery outcomes. While service measures such as improved communication and flexible delivery options are essential for enhancing customer experience, they may also introduce operational complexities that contribute to delays.

4.6 Gradient Boosting and Random Forest

To strengthen the predictive capability of the study beyond traditional statistical techniques, advanced machine learning models were implemented using the Orange Data Mining tool. The workflow began with data input and preprocessing using the Select Columns module, followed by model training using multiple learners. The performance of these models was evaluated using the Test and Score module.

Table 16: Gradient Boosting and Random Forest Performance

e	AUC	CA	F1	Precision	Recall	MCC
Random Forest	0.690	0.621	0.620	0.620	0.621	0.239
Gradient Boosting	0.682	0.613	0.613	0.614	0.613	0.227
Logistic Regression	0.650	0.609	0.609	0.611	0.609	0.219
Decision Tree	0.580	0.563	0.563	0.564	0.563	0.125

Interpretation:

Random Forest emerges as the best-performing model with the highest AUC (0.690) and accuracy (62.1%). This indicates a better ability to distinguish between delayed and non-delayed deliveries compared to other models. Gradient Boosting follows closely with an AUC of 0.682 and accuracy of

61.3%. Logistic Regression, although slightly lower in performance (AUC = 0.650), remains a reliable and interpretable model. Decision Tree shows the lowest performance (AUC = 0.580), indicating that a single-tree model is less effective in capturing the complexity of delivery delay patterns.

Inference:

Random Forest and Gradient Boosting outperform Logistic Regression and Decision Tree, confirming that delivery delays are influenced by complex, non-linear relationships among operational, technological, and service variables. The moderate performance across all models reinforces the conclusion that delivery delays are influenced by multiple interacting factors. Businesses can use these models as early warning systems to identify high-risk deliveries.

5. Findings

The data collected through a structured questionnaire distributed via Google Forms. The statistical analysis was carried out using Jamovi and the Orange Data Mining tool. The purpose of this chapter is to interpret the results in line with the three research objectives and present clear, practical insights into how delivery delays are perceived and experienced by Gen Z consumers in e-commerce.

Demographic and Descriptive Findings

The majority of respondents (53.26%) were between 22 and 25 years old, the core of the Gen Z online shopping community. Female respondents made up 56.32% and male respondents 43.68%, providing a near-balanced gender distribution. Students were the largest occupational group at 48.83%. Amazon was the most preferred platform (56.75%), indicating that brand reputation and reliability play a decisive role in platform selection among Gen Z consumers. UPI dominated as the preferred payment mode (65.13%), indicating a strong shift toward digital and cashless transactions. Most significantly, 52.11% of respondents confirmed that their most recent online order was delivered late.

Reliability Analysis

All Cronbach's Alpha values exceeded the required threshold of 0.70. Operational Factors scored 0.792 (acceptable), AI-Based Technology Monitoring scored 0.902 (excellent), and Service Measures scored 0.898 (good to excellent). These values confirm that the questionnaire was consistent, dependable, and trustworthy for further analysis.

Correlation Analysis

The Pearson correlation matrix revealed meaningful and statistically significant relationships between all three key variables ($p < 0.001$). Operational Factors and AI-Based Technology Monitoring showed a moderate positive correlation ($r = 0.503$). Operational Factors and Service Measures had a strong positive correlation ($r = 0.637$). AI-Based Technology Monitoring and Service Measures recorded the strongest correlation ($r = 0.737$), confirming that technology adoption has the most significant positive impact on service quality.

Regression and Machine Learning Findings

The binomial logistic regression model was statistically significant overall ($\chi^2 = 14.8$, $p = 0.002$). Operational Factors were found to be the most significant predictor of delivery delays ($\beta = -1.127$, $p = 0.001$, OR = 0.324). AI-Based Technology Monitoring, while showing a negative directional trend, was not statistically significant on its own ($p = 0.178$). Service Measures were found to have a statistically significant positive association with delays ($\beta = 0.755$, $p = 0.048$, OR = 2.127). Machine learning models, Gradient Boosting (AUC = 0.682) and Random Forest (AUC = 0.690), both outperformed the baseline Logistic Regression model (AUC = 0.641).

Overall Findings

- Delivery delays are a widespread and real-world issue. More than half of all respondents (52.11%) personally experienced a delay in their most recent online order.
- Operational gaps are the primary driver of delays. Improving core logistics processes like order processing, inventory management, and last-mile delivery has the greatest impact on preventing late deliveries.
- Technology monitoring is valued by customers and plays a directional role in reducing delays, but it cannot compensate for weak operational systems. It functions as a multiplier, not a substitute.
- Service expectations among Gen Z consumers are high, and this group is particularly sensitive to gaps between promised and actual delivery performance.
- Machine learning models like Logistic Regression, Random Forest, and Gradient Boosting can identify high-risk orders early, giving companies the ability to intervene proactively before a delay becomes a customer problem.
- All three study variables are strongly interconnected and reinforce each other, confirming the need for an integrated improvement strategy.

6. Conclusion

This study set out to understand how delivery delays in e-commerce affect Gen Z consumers and what can be done to prevent them. Using data collected from 261 respondents through a structured questionnaire, the study analysed three key dimensions, operational factors, AI-based technology monitoring, and service measures to build a customer-focused risk assessment framework for e-commerce supply chain deliveries.

The findings lead to one overarching and actionable conclusion: delivery delays are a real, widespread, and operationally driven problem. Over 52% of respondents experienced a delay in their most recent online order, and the data consistently confirms that poor logistics processes, not a lack of technology, are the primary driver of those delays. When operations improve, delays reduce.

The Role of Technology

Technology has an important but clearly secondary role to play. AI-based monitoring tools are trusted by customers and do contribute to reducing delays directionally, but only when they are backed by solid operational foundations. A tracking system can tell a customer exactly where their parcel is stuck but it cannot resolve the problem at the warehouse or clear the road for the delivery vehicle. E-commerce companies must understand this distinction and avoid treating technology as a shortcut. It is a multiplier, not a substitute for good operations.

Service Quality and Gen Z Expectations

Gen Z consumers are a demanding, digitally native audience. They expect fast, reliable, and transparent delivery as a basic standard not a premium feature. When their expectations are not met, they notice it more acutely than older consumer groups, and the data confirms this heightened sensitivity. This study shows that once companies get their operations and technology right, service satisfaction follows naturally.

Predictive Modelling for Proactive Delay Management

The machine learning models developed in this study, particularly the Random Forest (AUC = 0.690, CA = 62.1%) and Gradient Boosting models (AUC = 0.682, CA = 61.3%) demonstrate that it is possible to predict which orders are at risk of delay before they even ship. These models are already practically useful for prioritising high-risk orders, allocating better carrier resources, and proactively managing customer expectations. Incorporating additional variables such as real-time traffic conditions, weather disruptions, and delivery partner efficiency ratings would further enhance predictive accuracy.

Suggestions for E-Commerce Firms and Supply Chain Stakeholders

- Strengthen last-mile delivery networks, especially in semi-urban areas where a large and rapidly growing customer base remains underserved by current logistics infrastructure.
- Integrate AI-based monitoring systems directly into operational workflows so that automated alerts lead to real-time corrective actions not just passive status notifications to the customer.
- Leverage the predictive models developed in this study to flag high-risk orders at the point of purchase and assign them to priority fulfilment lanes with enhanced carrier allocation.
- Invest in proactive and transparent customer communication. A delay that is communicated early and managed professionally is significantly less damaging to customer trust than a silent service failure.
- Invest in training warehouse and logistics staff alongside technology adoption, since human errors in packing, sorting, and dispatch remain a key and addressable source of delivery delays.
- Conduct periodic reviews of delivery performance data, particularly for semi-urban delivery zones, to identify recurring delay patterns and address them systematically rather than reactively.
- Adopt an integrated improvement strategy rather than isolated fixes: operational efficiency, technology monitoring, and service quality must advance together for meaningful and lasting reductions in delivery delays.

References

1. Tang, Y. M., Chau, K. Y., Kuo, W. T., & Liu, X. X. (2023). IoT-Based Information System on Cold-Chain Logistics Service Quality (ICCLSQ) Management in Logistics 4.0. Information Systems Frontiers.
2. Islam, K. F., et al. (2025). Explainable Machine-Learning Framework for Predicting Delivery Delays and Risk in Smart Supply Chains. 2025 International Conference on Quantum Photonics, Artificial Intelligence, and Networking (QPAIN).
3. Hudnurkar, M., Renji, K. M., Ambekar, S., Sahu, G., & Joseph, K. M. (2024). Predicting Delays for Truck Delivery Logistics: An Application of AI and ML. 2024 Ninth International Conference on Science Technology Engineering and Mathematics (ICONSTEM).
4. Mirzaei, H., Daneshvar, A., & Nahavandi, B. (2025). Predicting the duration of goods transportation delays based on machine learning methods. Modern Supply Chain Research and Applications, 7(3), 404–423.
5. Rezki, N., & Mansouri, M. (2024). Management Systems in Production Engineering, 32(3), 345–356.
6. Jain. (2025). Predicting Delivery Outcomes in Supply Chain Management Using Machine Learning: A Random Forest Classifier Approach. International Journal of Progressive Research in Engineering Management and Science.
7. Kandula, S., Krishnamoorthy, S., & Roy, D. (2021). A prescriptive analytics framework for efficient E-commerce order delivery. Decision Support Systems, 147, 113584.
8. Wani, D., Singh, R., Khanapuri, V. B., & Tiwari, M. K. (2022). Delay Prediction to Mitigate E-commerce Supplier Disruptions using Voting Mechanism. IFAC-PapersOnLine, 55(10), 731–736.
9. Kaul, D., & Khurana, R. (2022). AI-Driven Optimization Models for E-commerce Supply Chain Operations. International Journal of Social Analytics Norislab Publishing, 07.

10. Ahmed, K. R., et al. (2025). Deep learning framework for interpretable supply chain forecasting using SOM ANN and SHAP. Scientific Reports, 15(1).
11. Huq, M. R., et al. (2026). Integrating machine learning and explainable AI for decision support in supply chain management. Journal of Engineering, 2026, Article 4839375.
12. Fei, L.-G., Liu, X., Jin, Y.-C., & Su, M. (2025). Reconstruction of Logistics Services in Cross-Border E-Commerce and Consumer Continuance Intention on Platforms. Journal of Theoretical and Applied Electronic Commerce Research, 20(3), 251.
13. Setiyawan, A., He, Y., & Sastri, R. (2025). Investigating the Role of Logistics Delivery Services in Shaping Customer Satisfaction. Journal of Theoretical and Applied Electronic Commerce Research, 20(4), 345.
14. Uvet, H. (2020). Importance of Logistics Service Quality in Customer Satisfaction: An Empirical Study. Operations and Supply Chain Management: An International Journal.
15. Ramos Ríos, J., Manotas Duque, D. F., & Osorio Gómez, J. C. (2019). Operational supply chain risk identification and prioritization from SCOR model. Ingenieria Y Universidad, 23(1).