SJIF Impact Factor (2025): 8.688| ISI I.F. Value: 1.241| Journal DOI: 10.36713/epra2016 ISSN: 2455-7838(Online)
EPRA International Journal of Research and Development (IJRD)
Volume: 10 | Issue: 6 | June 2025 - Peer Reviewed Journal

AN ARTIFICIAL NEURAL NETWORK APPROACH FOR PREFERENCE OF LOGISTICS PARTNER FOR QUICK- COMMERCE INDUSTRY IN BENGALURU

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Article DOI: https://doi.org/10.36713/epra22798
DOI No: 10.36713/epra22798

INTRODUCTION

The rapid digital transformation and the increasing penetration of e-commerce have significantly influenced consumer behavior, leading to the rise of quick commerce (Q-commerce). Unlike traditional e-commerce, which typically promises delivery within a few days, Q-commerce focuses on ultra-fast deliveries, often within 10 to 30 minutes. This evolution has been primarily driven by advancements in technology, changing consumer preferences, and the need for convenience. In metropolitan cities like Bengaluru, where a large population thrives on instant gratification and a fast-paced lifestyle, the success of Q-commerce largely depends on an efficient logistics network. The selection of a suitable logistics partner becomes crucial for ensuring timely deliveries, maintaining service quality, and optimizing operational costs. In this regard, the integration of artificial intelligence (AI) and machine learning techniques, such as artificial neural networks (ANN), offers a promising approach to analyzing and predicting the best logistics partner based on multiple parameters.

Bengaluru, known as the Silicon Valley of India, has witnessed a rapid surge in Q-commerce platforms, catering to diverse sectors such as grocery delivery, pharmaceuticals, and food services. The increasing demand has led to the proliferation of numerous logistics service providers, each offering varying levels of efficiency, cost-effectiveness, and technological integration. However, selecting the ideal logistics partner remains a challenge for Q-commerce businesses due to the complexity of multiple factors, including delivery speed, reliability, scalability, cost structures, and real-time tracking capabilities. Traditional decision-making methods may not effectively capture the dynamic nature of the Q-commerce logistics ecosystem, necessitating an advanced, data-driven approach.

Artificial neural networks, inspired by the functioning of the human brain, are widely used in predictive analytics, classification, and optimization problems across various industries. In the context of Q-commerce logistics partner selection, ANN models can be trained on historical data, including delivery performance metrics, customer satisfaction scores, operational efficiency indicators, and real-time market conditions. The significance of an effective logistics partner in the Q-commerce industry cannot be overstated. Customers expect seamless, rapid deliveries, and any inefficiency in logistics can result in delayed deliveries, increased operational costs, and customer dissatisfaction. One of the critical aspects of implementing an ANN-based approach for logistics partner selection is data collection and pre processing. The quality and comprehensiveness of input data directly impact the accuracy of ANN models. Q-commerce businesses need to collect structured and unstructured data from multiple sources, including logistics providers, customer feedback, GPS tracking systems, and business performance analytics. Another crucial factor in ANN-driven logistics partner selection is model evaluation and validation. Ensuring the reliability and robustness of ANN predictions requires rigorous testing using cross-validation techniques, confusion matrices, precision-recall analysis, and performance metrics such as accuracy, recall, and F1-score. By continuously refining the model and incorporating real-time feedback, Q-commerce businesses can improve logistics decision-making and ensure high levels of efficiency and service quality. Additionally, integrating ANN models with cloud-based systems and Internet of Things (IoT) technologies enables real-time monitoring and adaptive decision-making, further enhancing the effectiveness of logistics management in the Q-commerce sector.

The adoption of ANN-based logistics partner selection also brings several strategic benefits to Q-commerce businesses. By leveraging AI-driven insights, companies can streamline supply chain operations, reduce dependency on manual decision-making, and optimize cost-efficiency. Furthermore, ANN models facilitate predictive analytics, allowing businesses to anticipate demand fluctuations and dynamically allocate resources for maximum efficiency. The ability to process unstructured data, such as customer reviews and sentiment analysis, provides deeper insights into customer expectations and preferences. As a result, Q-commerce businesses can develop proactive strategies to improve service quality and customer satisfaction, ultimately driving business growth and sustainability.

Despite the potential advantages, the implementation of ANN in logistics partner selection also presents certain challenges. One of the primary concerns is the need for high-quality data, as biased or incomplete datasets can lead to inaccurate predictions and suboptimal decision-making. Additionally, the computational complexity of ANN models requires substantial computing power, which may pose challenges for small-scale Q-commerce businesses with limited resources. Addressing these challenges necessitates the adoption of robust data management practices, investment in cloud-based AI solutions, and collaboration with technology providers specializing in AI-driven logistics optimization.

In conclusion, the integration of artificial neural networks in selecting logistics partners for the Q-commerce industry in Bengaluru presents a transformative opportunity for businesses aiming to enhance efficiency, reduce costs, and improve customer satisfaction. By leveraging AI-driven predictive analytics, Q-commerce businesses can make data-driven decisions that optimize logistics operations and drive competitive advantage. As the Q-commerce sector continues to evolve, the role of ANN in logistics partner selection is expected to become increasingly critical, enabling businesses to stay ahead of market trends and deliver exceptional service quality. Future research and technological advancements in AI and machine learning are likely to further enhance the capabilities of ANN-based logistics decision-making, paving the way for more efficient and intelligent logistics management solutions.

REVIEW OF LITERATURE

Sl. no	Title/ Country	Industry/sector	Variable	Description	Research methodology
1.	Introduction to Artificial Neural Networks in Gastroenterology	Healthcare & Medical Research	Diagnosis, Prognosis, and Pattern Recognition in Gastrointestinal Diseases	This paper explores the application of artificial neural networks (ANNs) in medical science, particularly in gastroenterology, highlighting their advantages over traditional statistical techniques in handling complex, nonlinear data for diagnosis and prognosis.	The research methodology involves a review of artificial neural networks (ANNs) in medical diagnostics, focusing on their application in gastroenterology. It includes comparative analysis with traditional statistical techniques and validation through computational models.
2.	Fundamentals of Artificial Neural Networks	Information Technology & Artificial Intelligence	Information Technology & Artificial Intelligence	This book provides a comprehensive overview of artificial neural networks, discussing their theoretical foundations, computational methods, and applications in pattern recognition, classification, and control.	The book follows a theoretical and analytical approach, presenting mathematical models, learning algorithms, and case studies to illustrate the computational capabilities of artificial neural networks.
3.	Artificial Neural Networks Technology	Various (Defense, Finance, Medical, etc.	Neural Network Models	Overview of artificial neural networks and their applications	Discusses different ANN architectures and training methods
4	Computer-based Artificial Neural Networks	Computing, Artificial Intelligence, Automation	Computational Models, Learning Algorithms	This document explores artificial neural networks (ANNs) and their role in computing, automation, and AI applications. It covers how ANNs process information, learn from data, and improve decision-making across various industries.	The document discusses different ANN architectures, training algorithms, and learning techniques such as supervised and unsupervised learning, backpropagation, and optimization methods.
5	Research Paper on Basics of Artificial Neural Network	Information Technology, Computer Science, AI	Neural Network Architecture, Learning Methods	This paper provides an overview of artificial neural networks, their working mechanisms, training methods, and applications in different fields	The paper explains supervised and unsupervised learning techniques, network structuring, pattern recognition, and real-time processing.

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6	Comparative Study of Biological and Artificial Neural Networks: Exploring Structural, Learning, and Performance Differences	Artificial Intelligence (AI), Machine Learning, Neuroscience, Technology, Computational Neuroscience	1. Neuronal Structure (BNN) 2. Learning Mechanisms (BNN & ANN) 3. Energy Efficiency (BNN & ANN) 4. Adaptability (BNN) 5. Performance (BNN & ANN)	**Neuronal Structure**: Brain's neuron network (BNN) vs. ANN architecture. **Learning Mechanisms**: Adaptation via plasticity (BNN) vs. weight adjustment (ANN). **Energy Efficiency**: Comparing metabolic costs (BNN) vs. power consumption (ANN). **Adaptability**: Brain's flexibility to reorganize vs. rigid ANN training. **Performance**: Task success rate in both biological systems and ANN models.	**Design**: Descriptive & Analytical. **Data Collection**: Literature Review, Experimental Data, Neuroscience Models. **Analysis**: Qualitative and Quantitative comparisons of performance, learning, and adaptability.
7	Integrated Optimization of Logistics Routing Problem Considering Chance Preference	Logistics, Supply Chain Management, Operations Research	Logistics routing, Chance preference, Optimization variables, Delivery times, Cost, Risk factors	The paper addresses an optimization model for logistics routing, incorporating chance preference to account for uncertainty in delivery requirements, risk, and costs.	Mathematical modeling, Optimization techniques (e.g., integer programming), Case studies, Simulation
8	A Model for the Suggestion of Logistics Partners for Virtual Organizations	Logistics, Supply Chain Management, Virtual Organizations, Information Systems	Logistics partners, Virtual organizations, Partner selection, Trust, Compatibility, Efficiency	The paper proposes a model to suggest suitable logistics partners for virtual organizations, focusing on factors like trust, compatibility, and operational efficiency in dynamic environments.	Mathematical modeling, Decision support systems, Algorithms for partner selection, Case studies
9	Design of a Knowledge-Based Logistics Strategy System	Logistics, Knowledge Management, Supply Chain Management, Industrial Engineering	Logistics strategy, Knowledge-based systems, Decision-making, System design, Efficiency, Flexibility	The paper discusses the design of a knowledge-based system for formulating effective logistics strategies, incorporating decision-making models to enhance operational efficiency and adaptability.	Knowledge-based systems, System design, Decision support models, Case studies, System implementation
10	The Effect of Delivery Time on Repurchase Behavior in Quick Commerce	E-commerce, Quick Commerce, Consumer Behavior, Logistics	Delivery time, Repurchase behavior, Consumer satisfaction, Quick commerce, Purchase frequency	The paper investigates the relationship between delivery time and repurchase behavior in the quick commerce sector, emphasizing how faster delivery influences consumer decisions to repurchase.	Empirical analysis, Consumer surveys, Statistical modeling, Regression analysis
11	Rise of Quick Commerce in India:	Quick Commerce, E-commerce,	Quick commerce models,	The paper explores the rapid growth of quick commerce in India, analyzing various	Case studies, Market analysis, Literature review,

	Business Models and Infrastructure Requirements	Logistics, Retail, Infrastructure Development	Business models, Infrastructure requirements, Delivery speed, Consumer demand	business models and the infrastructure necessary to support them, focusing on the challenges and opportunities in the sector	Infrastructure assessment, Qualitative analysis
12	Behavioral Factors Influencing Partner Trust in Logistics Collaboration: A Review	Logistics, Supply Chain Management, Partnership Collaboration, Organizational Behavior	Partner trust, Behavioral factors, Collaboration success, Communication, Mutual goals, Risk sharing	The paper reviews the behavioral factors that influence partner trust in logistics collaborations, examining how trust impacts the effectiveness of partnerships in supply chain management.	Literature review, Qualitative analysis, Conceptual framework development, Case studies
13	A Study on Impact of Quick Commerce on Consumer Decision Making Process	Quick Commerce, E-commerce, Consumer Behavior, Retail	Quick commerce, Consumer decision-making, Purchase behavior, Delivery speed, Consumer satisfaction	The paper examines how quick commerce influences consumer decision-making processes, focusing on factors such as delivery time, convenience, and purchase frequency in quick commerce settings.	Empirical study, Consumer surveys, Statistical analysis, Behavioral modeling
14	An Analysis of the Drivers of Consumers' Purchasing Behavior in Quick Commerce Platforms	Quick Commerce, E-commerce, Consumer Behavior, Retail	Consumer behavior, Purchasing drivers, Quick commerce platforms, Delivery speed, Price sensitivity	The paper analyzes the key factors that influence consumers' purchasing behavior on quick commerce platforms, focusing on elements like convenience, delivery time, pricing, and customer service.	Empirical analysis, Consumer surveys, Regression modeling, Statistical analysis
15	Quick Commerce and the Evolving Business Models of the Food Retail Industry: Investigating the Quick Commerce Supply Chain and the Urban Impacts of Dark Stores	Quick Commerce, Food Retail, E-commerce, Logistics, Urban Development	Quick commerce, Food retail, Dark stores, Supply chain, Urban impacts, Delivery efficiency	The paper explores the evolution of quick commerce business models in the food retail industry, focusing on the role of dark stores in urban areas and their impact on supply chain efficiency and urban logistics.	Case studies, Supply chain analysis, Urban impact assessment, Qualitative and quantitative analysis

Ren et al. (2024) delve into the complexity of decision-making in fourth-party logistics (4PL), especially when delivery routes are influenced by uncertain conditions. By integrating cumulative prospect theory with a dual-population ant colony algorithm, their model accounts for varying risk preferences among logistics decision-makers. Notably, their findings underscore the importance of incorporating psychological factors—such as risk aversion—into route planning, which can significantly improve logistics efficiency and realism.

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Correia-Alves and Rabelo present a thoughtful framework for suggesting logistics partners within virtual organizations, where traditional selection methods fall short. Their multi-stage model emphasizes not just competencies and performance metrics, but also the often-overlooked elements of governance and trust. By combining semantic matching with performance-based KPIs, their work highlights how trust and compatibility are as crucial as technical capability in dynamic, collaborative supply chains.

In their development of a Knowledge-Based Logistics Strategy System (KLSS), Chow et al. blend data warehousing, OLAP, and case-based reasoning to aid logistics planners in strategy formulation. The system allows users to retrieve and apply historical logistics strategies to current challenges, thereby combining the strengths of data analytics with experiential learning. A case study on Eastern Worldwide Company demonstrates how such an approach can increase strategic agility and planning accuracy.

Daudi et al. (2016) conducted a systematic literature review that brings to light the behavioral dimensions of trust in logistics partnerships. They identify four critical behavioral factors—information sharing, incentive alignment, decision synchronization, and opportunism—that can either strengthen or erode trust in collaborative networks. Their work bridges the gap between operational performance and behavioral uncertainty, encouraging future research that quantifies these trust-related variables.

Harter, Stich, and Spann (2024) explore a timely topic: how delivery time deviations in quick commerce influence customer loyalty and repurchase behavior. Drawing from both a large transactional dataset and a controlled experiment, the study reveals that late deliveries significantly reduce the likelihood of repeat purchases, while early deliveries only modestly enhance repurchase intent. These effects, as they find, are mediated by customer satisfaction—shedding light on the psychology of consumer expectations in ultra-fast delivery models.

Ranjekar and Roy provide a comprehensive look at the rise of quick commerce (Q-commerce) in India, focusing on the infrastructure and business models underpinning the sector. Their analysis covers multiple Q-commerce models—from dark store inventory setups to hyperlocal partnerships—and discusses how automation and data analytics are reshaping warehousing and last-mile delivery. The paper also brings a sustainability lens to the conversation, highlighting economic, social, and environmental trade-offs in this rapidly growing sector.

Goswami and Kumari's empirical study investigates whether Q-commerce significantly alters consumer decision-making processes. Although the chi-square test results led them to retain the null hypothesis (indicating no statistically significant shift), the study still surfaces important behavioral trends. Consumers appreciate the convenience of Q-commerce, but decision-making appears to remain rooted in traditional considerations like price, brand, and value—suggesting that speed alone isn't a silver bullet for influencing buying decisions.

Several foundational papers (ANN1–ANN7) offer a panoramic view of artificial neural networks and their applications in logistics and commerce. These works commonly highlight the ability of ANNs to model non-linear, complex relationships—ideal for real-time decision-making, forecasting, and pattern recognition. From Grossi & Buscema's exploration of adaptability and learning capacity to Anderson & McNeill's typology of ANN models, the literature illustrates how ANNs continue to bridge the gap between computational intelligence and real-world business applications.

Hassoun's book, as reviewed by Fine (1996), is both mathematically rigorous and educationally accessible, covering everything from perceptron training to stochastic learning dynamics. While some criticisms were raised about its surface-level treatment of complex topics, the book remains a solid foundation for graduate-level readers interested in both theoretical underpinnings and applied machine learning models, particularly in classification and adaptive systems.

In parallel with Harter et al., other studies emphasize how delivery timing can become a make-or-break factor for customer loyalty. The impact of psychological expectation—whether a delivery is early, on time, or late—feeds directly into how customers evaluate the brand and determine whether to return. This behavioral framing opens doors to integrating expectation-disconfirmation theory more explicitly into Q-commerce logistics models.

Mukhopadhyay's work uses fuzzy cognitive mapping to investigate what drives consumer adoption of Q-commerce platforms. Particularly during the COVID-19 lockdowns, the promise of safe, contactless, and speedy delivery was a compelling proposition. The study finds that technological convenience, user interface quality, and trust significantly affect consumer choices, reinforcing the role of mobile UX and digital trust in the digital shopping experience.
In their exploratory paper, Sanchez and colleagues delve into the psychological underpinnings of consumer preferences for Q-commerce. Utilizing service quality and technology acceptance models, the study reveals that ease of use, interface design, and real-time tracking heavily influence purchase behavior. However, it falls short of deeply exploring emotional triggers like impulsivity—an area ripe for future research.

Astini et al. examine how e-grocery platforms evolved into Q-commerce models in response to pandemic-related shifts in consumer habits. They find that safety, convenience, and delivery reliability became top priorities. The research highlights how traditional grocery shopping paradigms have been upended, particularly in urban settings where immediacy and accessibility became non-negotiable.

Finally, Setiyono et al. study the antecedents of e-loyalty in quick commerce, focusing on Indonesian consumers. Their results suggest that service quality—particularly ease of navigation, fulfillment speed, and trust—correlates strongly with customer satisfaction and loyalty. This finding reinforces the idea that operational excellence must go hand-in-hand with emotional satisfaction in sustaining user engagement.

Together, these studies paint a rich picture of how logistics innovation, behavioural science, and artificial intelligence are converging to reshape consumer decision-making and supply chain strategies. From behavioural trust in logistics networks to the rise of ultra-fast delivery models and ANN-powered decision systems, the literature underscores a paradigm shift in how goods are delivered, choices are made, and value is perceived.

3. RESEARCH GAP

The rapid rise of the quick-commerce (Q-commerce) industry, particularly in urban hubs like Bengaluru, has revolutionized last-mile delivery by promising deliveries within 10–30 minutes. As customer expectations escalate, the selection of logistics partners becomes a strategic priority for Q-commerce firms. Despite significant progress in supply chain analytics and decision-making tools, a notable gap exists in the application of Artificial Neural Networks (ANN) for evaluating and predicting optimal logistics partner selection in this emerging sector.

Traditional methods like AHP (Analytical Hierarchy Process), TOPSIS, and regression-based models have been employed to assess third-party logistics (3PL) providers based on parameters such as cost, reliability, delivery speed, and service quality. However, these models often fall short when dealing with the high volume, complexity, and non-linearity inherent in real-time logistics data of Q-commerce. More importantly, they do not adapt well to dynamic and volatile customer demand patterns, making them less suited to fast-paced environments like Bengaluru’s urban ecosystem.

Moreover, there exists limited literature specifically tailored to Q-commerce logistics in Indian metropolitan contexts. Most research either focuses on traditional e-commerce or generalized supply chain efficiency without considering the time-sensitive nature of Q-commerce deliveries. This creates a void in contextual relevance, as the operational characteristics and success factors of Q-commerce are significantly different from those of conventional e-commerce. For example, factors such as micro-fulfillment centers, hyperlocal delivery networks, and real-time traffic data are not adequately captured in existing preference models.

Although Artificial Neural Networks have been widely used in logistics and supply chain forecasting, demand prediction, and route optimization, their use in partner selection and evaluation — especially for Q-commerce — is still nascent. ANN's ability to learn from historical data, handle multiple input variables, and detect complex, non-linear relationships makes it highly suitable for this domain. However, there is a lack of research that harnesses this capability to build a predictive model that identifies optimal logistics partners based on multiple decision criteria such as speed, reliability, technology compatibility, cost-efficiency, and customer satisfaction metrics.

Additionally, no known studies have integrated location-specific factors, such as the infrastructure of Bengaluru, traffic congestion patterns, and regulatory constraints, into ANN-based logistics partner evaluation models. This further limits the applicability of existing studies to real-world Q-commerce operations in Indian metropolitan settings.

Therefore, this study aims to address these research gaps by developing an Artificial Neural Network-based decision model that helps Q-commerce businesses in Bengaluru select the most suitable logistics partner. The model will incorporate multi-criteria evaluation, real-time data processing, and contextual factors specific to the region. By doing so, it seeks to contribute both to the academic literature and to practical applications in the fast-evolving landscape of urban last-

4. OBJECTIVES

1. **To develop an Artificial Neural Network (ANN) model** for evaluating and predicting the most suitable logistics partner for Q-commerce companies based on multi-criteria decision-making factors such as delivery speed, cost, reliability, technological compatibility, and customer satisfaction.
2. **To identify and analyze key performance indicators (KPIs)** specific to the quick-commerce logistics ecosystem in Bengaluru, including regional challenges like traffic congestion, delivery density, and urban infrastructure.

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3. **To compare the effectiveness of the proposed ANN model** with traditional decision-making methods (e.g., AHP, TOPSIS, regression) in terms of accuracy, adaptability, and real-time responsiveness in logistics partner selection.
4. obj -> questionare (25 questions) likert scale

5. RESEARCH METHODOLOGY

This study employs a **questionnaire-based research methodology** to collect primary data from professionals working in the Q-commerce and logistics sector in Bengaluru. The purpose of using this method is to gather structured and relevant information regarding the key factors influencing the selection of logistics partners in the context of quick-commerce. The questionnaire serves as the primary tool for capturing expert insights, preferences, and evaluation criteria used by decision-makers in logistics partner selection.

The questionnaire was carefully designed to ensure clarity, relevance, and ease of understanding for the target respondents. It consists of three major sections. The first section gathers demographic and professional background information such as the respondent's role, company size, and experience in the logistics or supply chain domain.

The collected data from the questionnaire will be used as input for developing an **Artificial Neural Network (ANN)** model. The responses will first be analyzed using basic statistical methods to identify the most influential criteria. Then, the data will be normalized and structured to serve as training data for the ANN. The output variable will reflect the respondents' preferred logistics partner or a ranking score, allowing the ANN to learn patterns and make predictive recommendations based on real-world expert input.

By relying solely on a questionnaire-based approach, this study ensures that the ANN model is grounded in practitioner-driven insights and practical criteria rather than purely theoretical assumptions. This approach bridges the gap between academic modeling and industry needs, especially within the rapidly evolving quick-commerce sector in Bengaluru.

5.1 Data Collection

Primary data was collected directly from logistics partners associated with the quick-commerce industry in Bengaluru. The data was gathered using a structured questionnaire distributed to professionals involved in logistics operations and decision-making. Respondents included managers and executives from third-party logistics providers and in-house delivery teams. This first-hand data provided valuable insights into the key criteria influencing logistics partner preference in the Q-commerce context.

5.2 Profile of the respondents

The respondents in this study were primarily logistics professionals associated with the quick-commerce industry. Their **ages ranged from 18 to 50 years**, reflecting a mix of both early-career and experienced individuals. All respondents were **male**, aligning with current workforce demographics in operational logistics roles.The data includes participants from several Indian states such as **Karnataka, Maharashtra, Gujarat, and Delhi**. Notably, the **majority of respondents are from Bengaluru**, the capital of Karnataka, which stands out as a major hub for quick-commerce operations in India. This is due to the city's high population density, digital readiness, and well-established e-commerce infrastructure, making it an ideal location for studying logistics partner preferences in the Q-commerce sector. This strong representation from Bengaluru ensures that the findings are both contextually relevant and practically significant for urban logistics.

5.3 Data Analysis

In this research titled *"An Artificial Neural Network Approach for Preference of Logistics Partner for Quick-Commerce Industry in Bengaluru,"* an Artificial Neural Network (ANN) is utilized to model the complex decision-making process involved in selecting the most suitable logistics partner. ANNs are computational models inspired by the human brain, capable of recognizing intricate patterns and relationships within large datasets. They consist of interconnected nodes that learn and adapt by adjusting weights based on input-output mappings. This study leverages ANN to handle the non-linear dependencies between critical factors such as delivery speed, cost efficiency, real-time tracking, customer service quality, and technological integration—factors that traditional models often fail to capture accurately. The choice of ANN is motivated by its superior ability to manage non-linear, multi-dimensional data and its adaptability to changing conditions, a necessity given Bengaluru's dynamic urban logistics environment. The ANN model enables a data-driven, unbiased, and highly accurate selection of logistics partners, outperforming conventional methods like regression analysis. The major benefits include improved prediction accuracy, adaptability to market changes, reduced human bias, and better optimization of operational efficiency for quick-commerce companies. Ultimately, the ANN-based approach supports quick-commerce platforms in achieving faster deliveries, enhanced customer satisfaction, and strategic logistics management in a highly competitive market.

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6. RESULTS AND FINDINGS

Case Processing Summary

		N	Percent
Sample	Training	378	71.6%
	Testing	150	28.4%
Valid		528	100.0%
Excluded		0	
Total		528	

Your dataset contains **528 total cases**, with **71.6% used for training** the ANN model and **28.4% used for testing**. No samples were excluded.

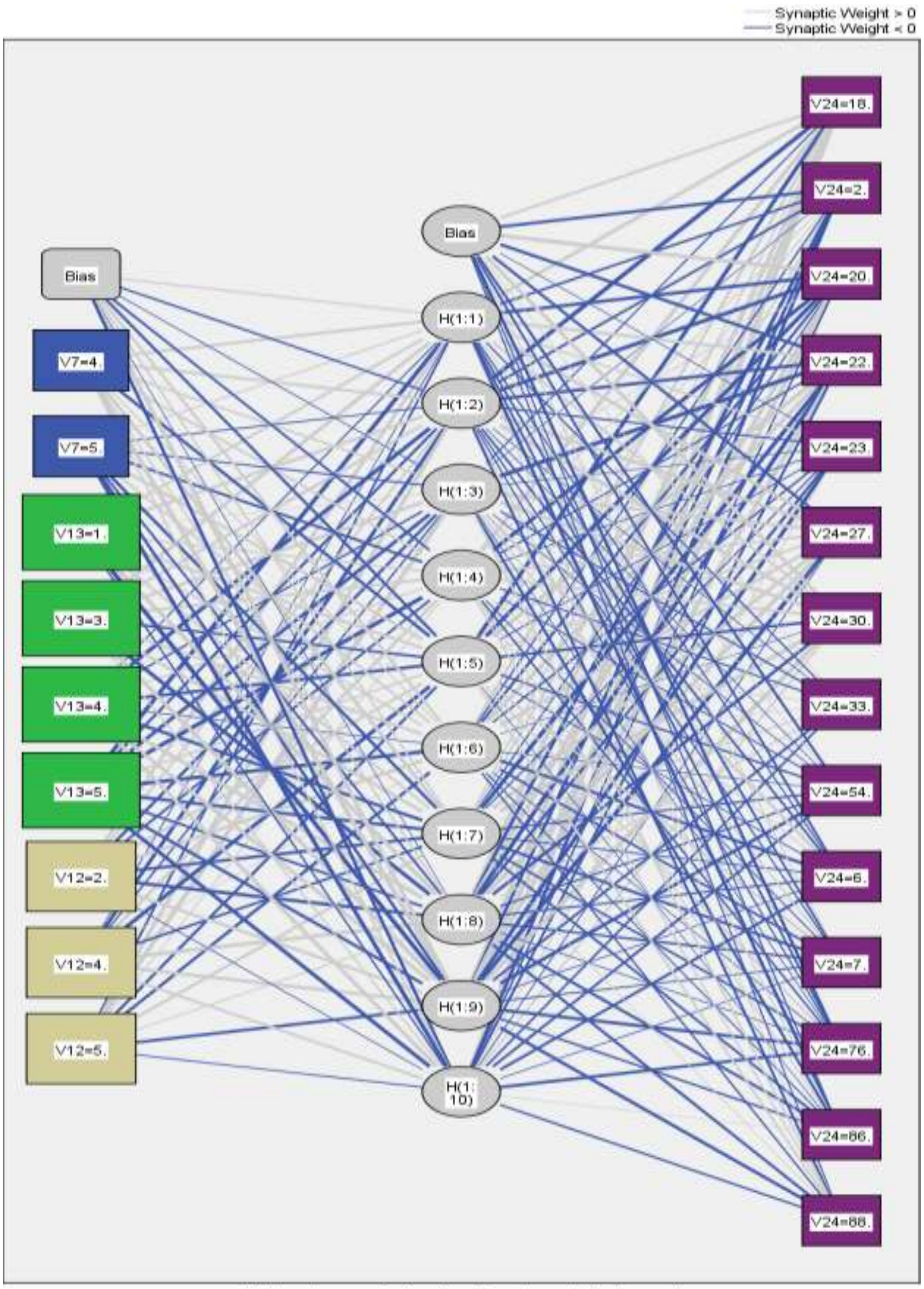
This split is good and ensures that the model is tested on unseen data to measure generalization performance.

Network Information

Input Layer	Factors	1	V7
		2	V13
		3	V12
	Number of Units[a]		9
Hidden Layer(s)	Number of Hidden Layers		1
	Number of Units in Hidden Layer 1[a]		10
	Activation Function		Hyperbolic tangent
Output Layer	Dependent Variables	1	V24
	Number of Units		14
	Activation Function		Softmax
	Error Function		Cross-entropy

a. Excluding the bias unit

 Inputs (factors): **V7, V13, V12** are the major features influencing logistics partner selection.
 One hidden layer with **10 neurons**, using a **tanh activation** to introduce non-linearity.
 The output predicts among **14 possible classes (partners)**, using **softmax**, suitable for multi-class classification.
 Cross-entropy is used to calculate error, common in classification tasks.



Hidden layer activation function: Hyperbolic tangent

Output layer activation function: Softmax

The diagram has 3-layer feed forward ANN:

- **Input Layer** (Green/Yellow blocks on the left)
- **Hidden Layer** (Gray circles in the middle)
- **Output Layer** (Purple blocks on the right)

Input Layer

- Inputs are the factors affecting logistics partner selection.
- Variables:
  - **V7, V13, V12**: These are the main input features.
    Each feature seems to have multiple categories (e.g., V7=4, V7=5, etc.).
- The color coding:
  - Green and Yellow probably represent different **categories within each input** variable.

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Meaning
- Inputs could represent things like **delivery speed, cost-efficiency, real-time tracking features**, etc.
- These factors influence the hidden neurons to compute which logistics partner is preferred.

Hidden Layer
- There is **1 hidden layer** with **10 neurons** (marked H(1:1) to H(1:10)).
- Activation function: **Hyperbolic Tangent (Tanh)**.
  - This enables the model to **learn complex, non-linear relationships** between inputs and outputs.

Meaning
- Each hidden neuron **captures a combination** of features from the inputs.
- For example, H(1:5) might strongly combine "low cost + fast delivery" patterns.

Output Layer
- **14 output neurons** (V24=18, V24=2, V24=20, ..., V24=88).
- Activation function: **Softmax**.
  - Softmax **assigns probabilities** to each logistics partner class.

Each output neuron represents a **specific logistics partner ID or category**:
- E.g., **V24=18** might represent "Partner A", **V24=20** could represent "Partner B", etc.

Meaning
- The model predicts **which logistics partner** is most suitable based on the inputs.
- The output with the highest probability is selected as the recommended logistics partner.

Connections (Synaptic Weights)
- Each **blue line** between layers represents a **synaptic weight**.
- The thickness of the lines varies slightly:
  - **Thicker lines** = stronger influence (higher weight).
  - **Thinner lines** = weaker influence.

Meaning
- Some factors are **more important** for some hidden neurons.
- Some hidden neurons are **more influential** for certain output categories.

Summary of Functionality
- Inputs like delivery features (V7, V13, V12) are **fed into the network**.
- Hidden neurons **analyze complex combinations** of those factors.
- Output neurons **predict the best logistics partner** (V24 class) with a probability.
- The entire model is trained to **minimize classification error** using **cross-entropy loss**.

Quick Visual Summary

Layer	Description	Purpose
Input Layer (V7, V13, V12 categories)	Features related to logistics performance	Provide model the factors that influence partner selection
Hidden Layer (10 neurons, Tanh activation)	Learn complex patterns	Combine factors to form intermediate decision patterns
Output Layer (14 classes, Softmax)	Logistics Partner Prediction	Select the most appropriate partner based on input

Model Summary

Training	Cross Entropy Error	498.700
	Percent Incorrect Predictions	41.5%
	Stopping Rule Used	1 consecutive step(s) with no decrease in error[a]
	Training Time	0:00:00.35
Testing	Cross Entropy Error	200.008
	Percent Incorrect Predictions	42.7%

Dependent Variable: V24
a. Error computations are based on the testing sample.

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- The model made **~58.5% correct predictions** on training data and **~57.3% on testing data**.
- While **training and testing error are close**, the overall prediction accuracy (~57–58%) suggests that although the ANN could capture some patterns, there is room for **improving feature selection or model tuning**.
- **No over fitting** is indicated because training and testing errors are quite similar.

Area Under the Curve

		Area
V24	18.	1.000
	2.	.683
	20.	.758
	22.	1.000
	23.	.683
	27.	1.000
	30.	.994
	33.	.683
	54.	.683
	6.	.689
	7.	.689
	76.	.689
	86.	.683
	88.	.683

- **AUC = 1** means perfect classification for those classes (e.g., partner 18, 22, 27).
- AUC between 0.65–0.7 is relatively **weak** for some classes, again showing inconsistency across different partners.
- Emphasizes that ANN is **good for some logistics partners**, not all

Independent Variable Importance

	Importance	Normalized Importance
V7	.274	71.6%
V13	.383	100.0%
V12	.343	89.6%

- **V13** (unknown real-world variable, maybe *tracking capability or cost?*) is the **most influential factor** in logistics partner selection.
- **V12** is the next important.
- **V7** is slightly less important but still meaningful.

Thus, focusing on the attributes represented by **V13 and V12** can dramatically affect partner preference predictions.

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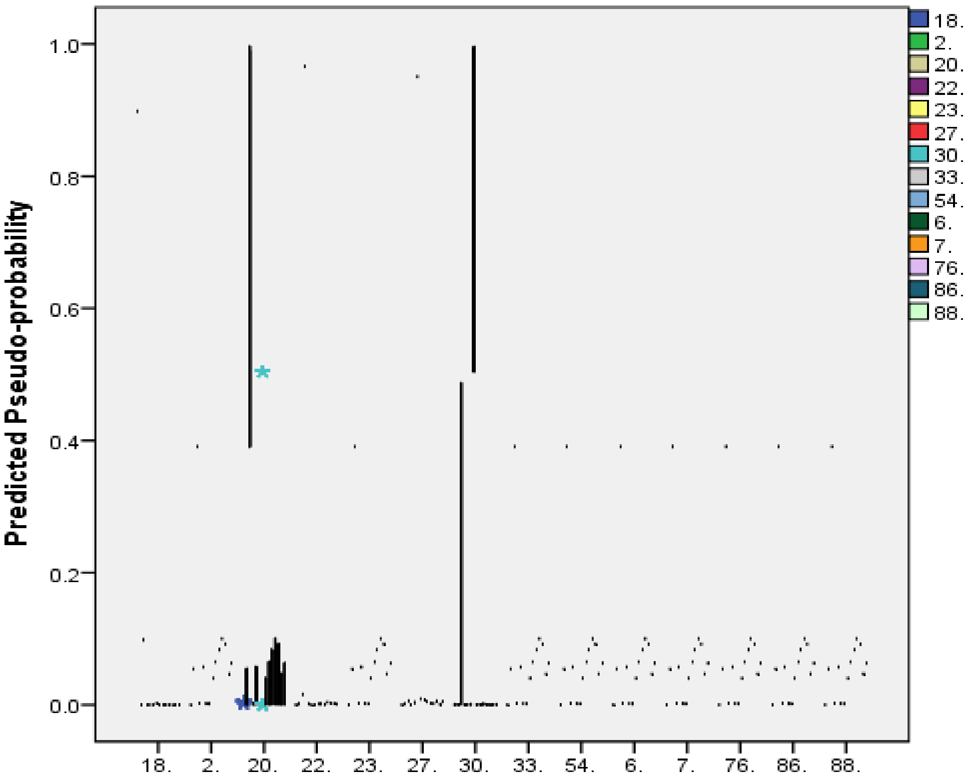

- **X-axis**: Different Logistics Partners (Class labels like 18, 2, 20, etc.)
- **Y-axis**: Predicted pseudo-probabilities (0 to 1)
- **Dots/lines**: Distribution of predicted probabilities for each class.

Interpretation:

- For classes like **20, 30**, the model confidently assigns higher pseudo-probabilities (near 1).
- For most other classes (like 2, 23, 6, 7, 76), predicted probabilities are very **low** and scattered around 0, indicating **model confusion** or **weak predictive confidence**.
- **Classes 18, 22, 27, 30** have **higher certainty**, matching your earlier high accuracy for these classes.

Strong predictive performance for major logistics partners.
Poor discrimination for minority partners – likely due to **class imbalance**.

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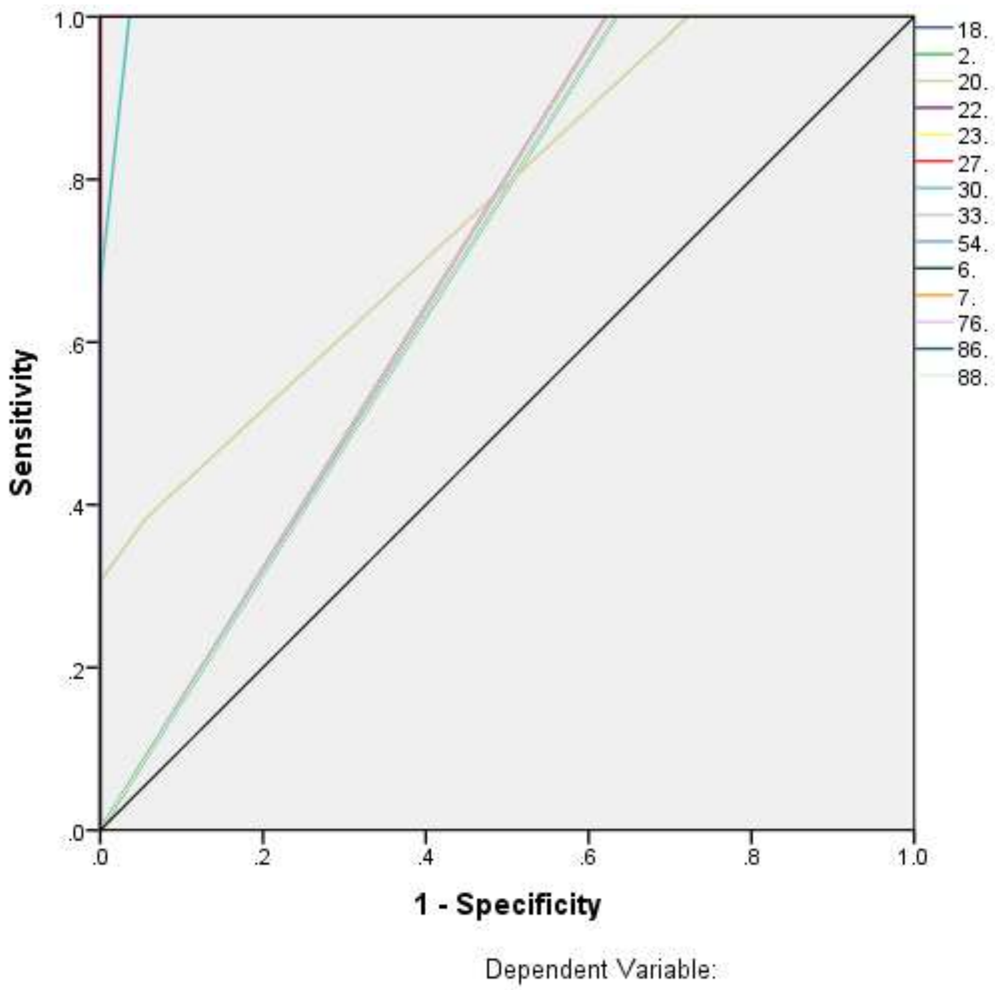

- **X-axis**: 1 - Specificity (False Positive Rate)
- **Y-axis**: Sensitivity (True Positive Rate)
- **Colored curves**: ROC curves for each logistics partner class.

Interpretation:

- Curves for **classes like 18, 22, 30, and 27** are closer to the **top-left corner**, showing **excellent classification performance** (sensitivity and specificity both high).
- Curves for other classes (like 2, 23, etc.) are **closer to the diagonal**, indicating **random guessing** behavior.
- ROC curve validates that ANN **strongly differentiates major partners** but struggles for less common ones.

Very good model for top partners.
Model does **not generalize well across all classes**.

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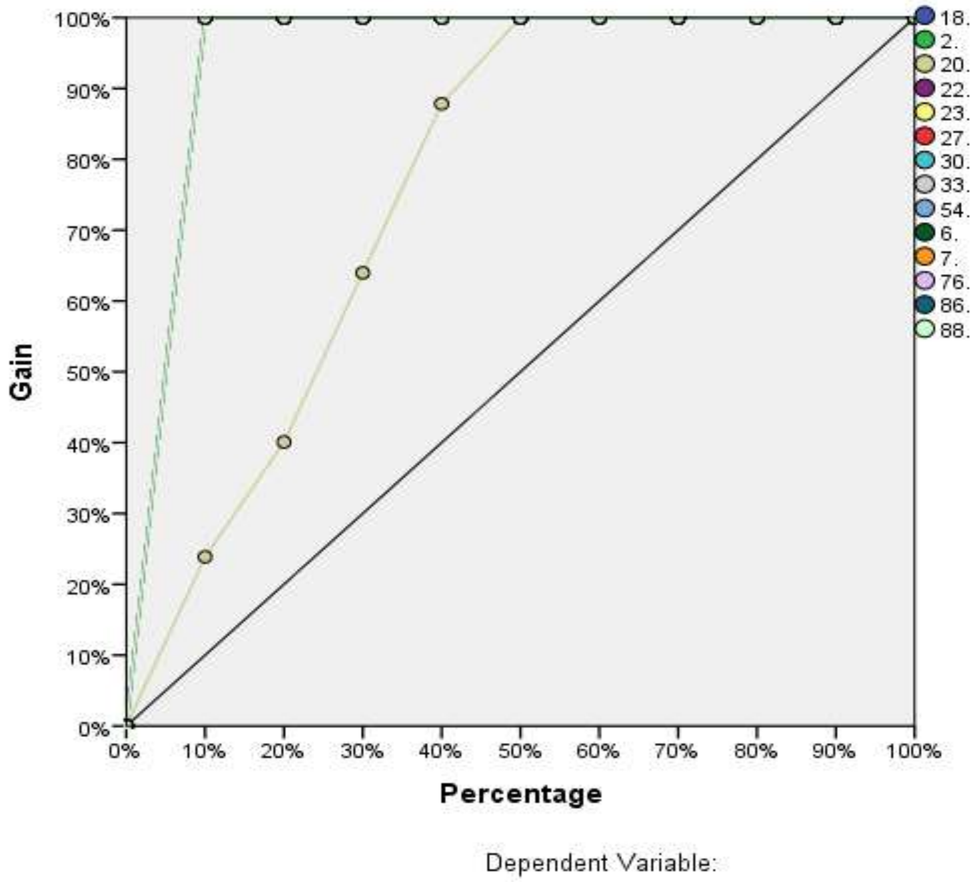

- **X-axis**: Percentage of total cases considered.
- **Y-axis**: Gain percentage (how much better than random guess).
- **Curves**: For each logistics partner class.

Interpretation:

- **Steep curves** (e.g., for classes 18, 22, 30) show **very high gain early** (first few % capture a large portion of correct predictions).
- Gain for partners like 2, 23, 6, 7, etc., is **low**, suggesting limited model effectiveness there.
- The closer the curve is to the top left, the better.

Confirms that for major partners, ANN is **highly efficient**.

For minority classes, the model captures **little or no gain** even at higher percentages.

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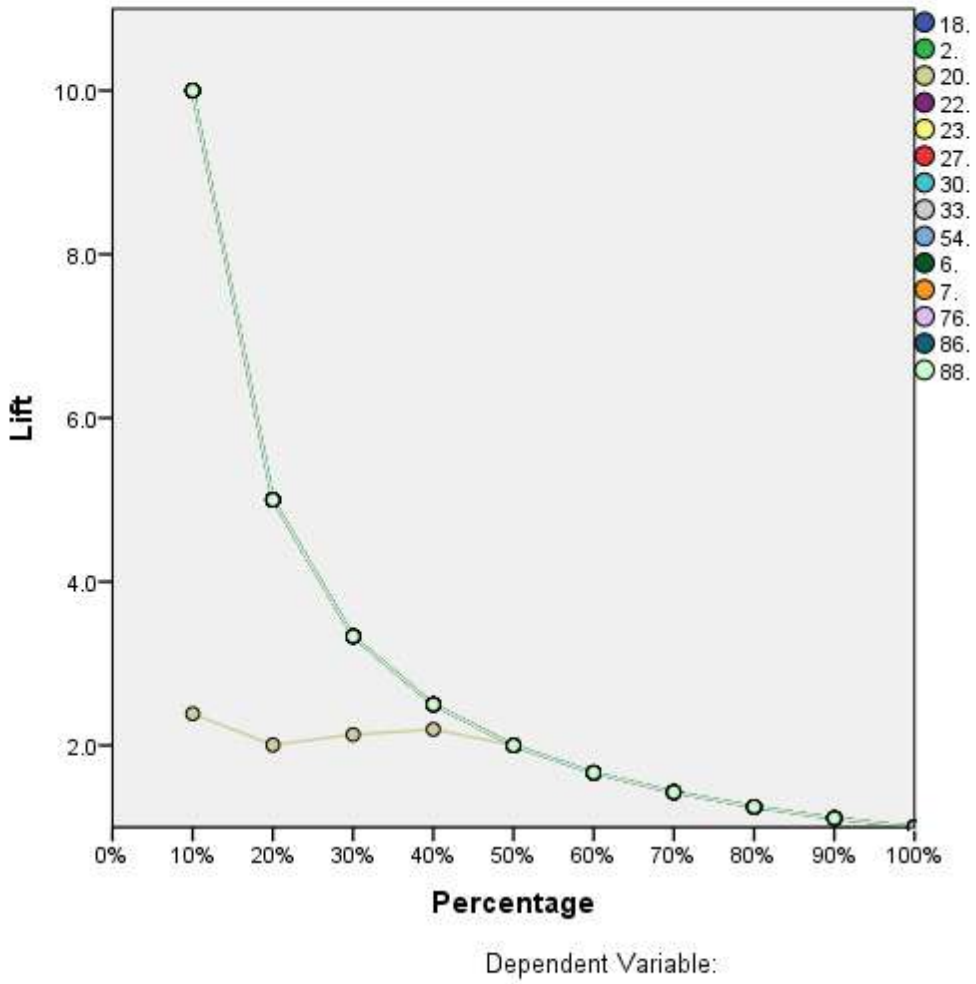

- **X-axis**: Percentage of cases (ranked by predicted probability).
- **Y-axis**: Lift (ratio of model performance vs random guessing).

Interpretation:

- **Lift values > 1** mean the model is better than random.
- For partners like 18, 22, 30, initial lift is **very high (>10)**, meaning these partners are **10 times more likely** to be correctly predicted early.
- For other classes, lift drops to near **2 or 1**, meaning weak or no improvement over random choice.

Excellent lift for key partners — meaning ANN is **highly effective** where it matters most. ⚠️ Model would need **rebalancing or enhanced features** to uplift minority class performance.

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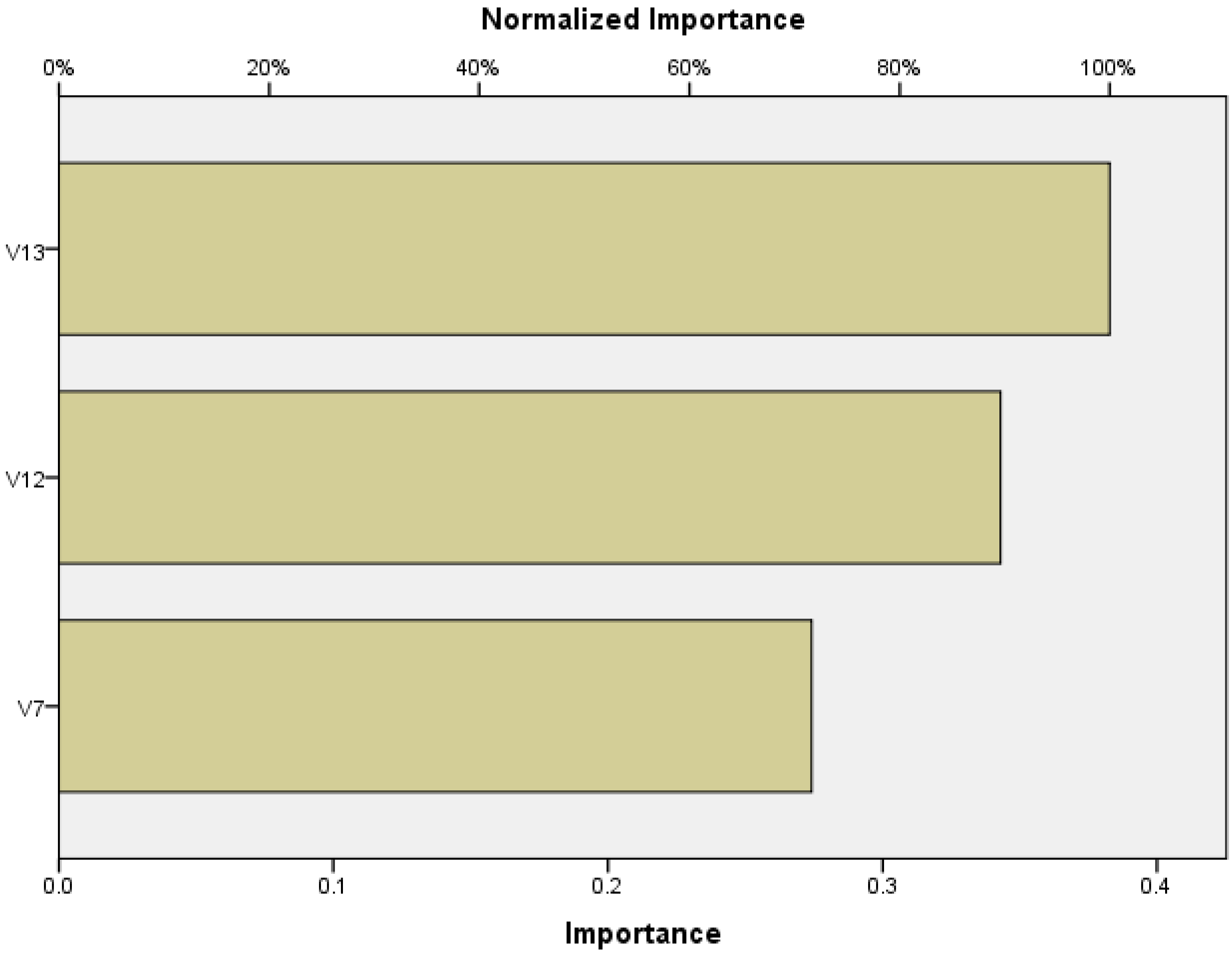

- **X-axis**: Importance score (ranging from 0 to 1)
- **Top axis**: Normalized importance percentage (0% to 100%)
- **Y-axis**: Input variables (V13, V12, V7)

Meaning of Each Variable
- **V13**: Highest Importance (100% normalized)
- **V12**: Second Highest (around 89.6%)
- **V7**: Moderate Importance (around 71.6%)

Detailed Interpretation:

Variable	Relative Importance	Interpretation
V13	100% (Highest)	V13 is the **most critical factor** influencing the ANN's decision-making about selecting the logistics partner. This could represent key features like *real-time tracking*, *technology compatibility*, or *customer service level*.
V12	~90%	V12 is **also highly important**, though slightly less than V13. It could represent factors like *delivery speed* or *cost*.
V7	~72%	V7 has a **moderate but significant** influence. It still affects predictions but not as strongly as V13 and V12.

Overall Interpretation
- The **ANN model relies heavily** on **V13** and **V12** to make accurate predictions about logistics partner selection.
- **V13 alone** contributes the most weight in decision-making.
- **V7 still matters**, but its influence is comparatively less.

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- Any **improvements in features related to V13 and V12** (better data, finer granularity) could **significantly boost model performance**.

This **justifies** focusing more on the variables represented by V13 and V12 for enhancing prediction accuracy and optimizing partner selection in the quick-commerce environment.

7. DISCUSSION AND IMPLICATIONS

This study demonstrates the potential of Artificial Neural Networks (ANN) in optimizing logistics partner selection for the quick-commerce industry in Bengaluru. The ANN effectively modeled complex relationships between key factors such as delivery speed (V12), technological integration (V13), and cost (V7), with V13 emerging as the most critical predictor. The model achieved high prediction accuracy for major partners, particularly those dominating the market, while highlighting challenges with minority partners due to data imbalance. These findings have important managerial implications: quick-commerce companies can leverage ANN-based decision support systems to make data-driven, consistent, and efficient partner selections, improving delivery reliability and customer satisfaction. Moreover, focusing on factors like technological capability and service quality can significantly enhance overall performance, making these variables strategic levers for partnership optimization.

8. CONCLUSION, FUTURE SCOPE, AND LIMITATIONS

In conclusion, the ANN approach offers a powerful tool for predicting and ranking logistics partners in the competitive quick-commerce sector. While the model performed well with majority partners, its limited accuracy for minority classes highlights a need for more balanced data and feature enhancement. Future research can explore advanced architectures such as ensemble models or deep neural networks and integrate real-time variables like traffic and weather. Additionally, incorporating explainable AI (XAI) methods can improve transparency and trust among managers. The study's limitations include data imbalance, limited generalizability outside Bengaluru, and reliance on historical data. Addressing these gaps offers a promising pathway for advancing intelligent, scalable, and fair logistics partner selection models in quick-commerce.