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(Review Article)

Predictive Order Routing and Fulfilment Optimisation Using CRM Customer Insights

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Abstract

The convergence of Customer Relationship Management (CRM) systems and predictive analytics is transforming order fulfilment and logistics operations. This review explores how CRM-derived insights, such as customer preferences, behaviour patterns, and transactional history, can optimise predictive order routing and intelligent fulfilment in modern commerce. Through an analysis of recent studies, theoretical models, and empirical results, it demonstrates that integrating CRM data with AI models significantly improves routing accuracy, reduces delivery times, and enhances customer satisfaction. Looking ahead, companies are already experimenting with real-time CRM platforms, privacy-first analytics, and IoT-driven fulfilment. These advances, together with emerging industry standards, are beginning to define what the next generation of smart logistics will look like.

Keywords: CRM analytics; Predictive order routing; Fulfilment optimization; AI logistics; Customer insights; Machine learning; Smart warehousing; Real-time CRM; Last-mile delivery; Federated learning

1. Introduction

The dynamics of modern commerce are undergoing a profound transformation, driven by rapid digitalisation, elevated customer expectations, and increasingly complex supply chains. At the heart of this transformation lies the growing integration of Customer Relationship Management (CRM) systems with predictive analytics, which together enable businesses to intelligently route orders and optimise fulfilment in near real-time. One particularly promising approach in this evolving landscape is the use of predictive order routing, powered by customer insights extracted from CRM systems, to forecast demand, personalise logistics, and enhance operational efficiency [1]. In today's competitive environment, businesses are expected to provide faster deliveries, accurate order fulfilment, and personalised customer experiences, all while minimising operational costs and carbon footprints. Walmart and Target have explored predictive routing combined with electric vehicle fleets, reducing last-mile emissions while optimising delivery schedules [2].

Traditional static routing and inventory allocation methods often fall short in addressing these complexities, especially when customers interact through multiple digital channels and expect adaptive service across every touchpoint [3]. Instacart, for instance, used CRM-driven demand prediction during the COVID-19 surge to scale from 1,200 to 14,000 support agents almost overnight, later automating processes to stabilise operations [4][5]. Recent pilots by Amazon and FedEx also illustrate the potential Amazon's tested humanoid delivery robots to reduce delivery bottlenecks, while FedEx's Roxo bot trials highlighted efficiency gains in urban last-mile delivery [6][7]. This illustrates how CRM-linked insights directly shape both workforce and routing efficiency. CRM systems, which house rich data on customer preferences, transaction history, behaviours, and feedback, offer a unique opportunity to shift toward predictive, insight-driven fulfilment networks [8].

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Beyond isolated use cases, what's happening is a structural shift: CRM tools powered by AI and machine learning are no longer just supporting marketing teams; they're starting to orchestrate logistics decisions end to end. This shift is part of the larger trend toward intelligent supply chains, a concept that integrates big data, artificial intelligence, and IoT-enabled sensors to make real-time decisions across the entire product lifecycle from demand planning to last-mile delivery [9].

Despite the growing interest and technological readiness, several key challenges and research gaps persist:

- Many CRM systems still function as isolated customer databases, with limited integration into logistics and supply chain operations.
- There is inconsistent usage of predictive analytics to influence fulfilment decisions across sectors.
- Businesses lack standardised frameworks or theoretical models for CRM-driven predictive routing.
- The ethical implications of using personal customer data in predictive modelling remain underexplored in logistics contexts [10].

Given these gaps, this review aims to provide a comprehensive, human-centred synthesis of research in predictive order routing and fulfilment optimisation using CRM customer insights. It will explore how data from CRM platforms, when coupled with AI/ML and operational data, can optimise:

- Inventory positioning,
- Fulfilment channel selection,
- Delivery routing,
- And demand forecasting.

The paper examines a curated set of key research studies and discusses theoretical models, algorithmic approaches, experimental evaluations, and emerging best practices that connect CRM insights to predictive logistics performance.

This article is structured as follows:

- A research summary table.
- Block diagrams and theoretical frameworks explaining data integration and routing optimisation.
- Experimental results with performance metrics, visualisations, and CRM-integrated use cases.
- Future research directions, followed by a conclusion, abstract, and keywords.

This review is written with both researchers and practitioners in mind, aiming to bridge academic findings with the realities of day-to-day supply chain and CRM decision-making.

2. Literature Review

Table 1 Key Research on Predictive Order Routing and Fulfilment Optimisation via CRM Insights

Study Focus / Objective	Methodology	Key Findings	Relevance to Research	Ref. No.
Explores the integration of social commerce and Industry 4.0 technologies to enhance customer experience.	Empirical and conceptual analysis combining digital commerce and smart technologies.	Demonstrates that integrating social commerce with Industry 4.0 enhances personalized engagement, customer insights, and satisfaction.	Highlights how modern tech convergence can elevate CRM and customer-centric strategies.	[11]
Develops a model to measure the impact of omnichannel information processing on digital shopping decisions.	Analytical model using survey data and validation through statistical techniques.	Omnichannel data processing improves user satisfaction and shopping decisions, especially with personalized content delivery.	Supports CRM systems' role in unified channel experiences to boost customer engagement.	[12]

Discusses strategies for customer success management to reduce churn and increase recurring revenue.	Case studies of leading SaaS companies implementing CSM strategies.	CSM drives business growth by reducing churn and enhancing lifetime customer value.	Emphasizes the shift from traditional CRM to proactive customer success approaches.	[4]
Conducts a systematic literature review on CRM-enabled data-driven decision-making in enterprises.	Systematic review of peer-reviewed literature using inclusion/exclusion criteria.	CRM acts as a core driver for strategic decision-making across marketing, sales, and operations.	Provides a consolidated view of CRM's value in enterprise-wide data utilization.	[13]
Examines AI and robotics applications in the oil and gas industry, focusing on digital transformation.	Industrial case studies and technical analysis.	AI and robotics optimize efficiency, safety, and customer service in critical infrastructure sectors.	Demonstrates sector-specific applications of intelligent systems that influence CRM and customer operations.	[14]
Applies machine learning techniques to CRM data to predict cross-selling opportunities in retail banking.	Predictive analytics using supervised learning on customer transaction datasets.	ML improves targeting accuracy, leading to higher cross-sell success rates.	Illustrates how AI-driven CRM analytics drive sales and personalization.	[15]
Analyzes the effect of AI-powered personalization on customer loyalty in e-commerce via meta-analysis.	Meta-analysis of empirical studies in e-commerce personalization.	Personalization significantly boosts customer loyalty, with AI playing a key role in real-time adaptation.	Reinforces the importance of AI in CRM systems for tailored customer retention strategies.	[16]
Identifies emerging trends in computer science relevant to business applications, including AI, IoT, and cloud.	Literature review across key subfields in CS with business relevance.	AI, IoT, and cloud computing will dominate future customer experience and operational tech.	Establishes the foundational tech landscape for CRM and intelligent fulfillment.	[17]
Investigates how customer experience in online shopping impacts satisfaction and loyalty.	Quantitative survey-based study with statistical analysis.	Positive digital customer experience has a direct impact on loyalty and repeat purchases.	Provides evidence for optimizing CRM features based on experience-driven metrics.	[18]
Explores the role of AI in optimizing supply chain processes, focusing on decision-making efficiency.	Review of industrial applications and case studies.	AI enables real-time decision-making, reducing delays and improving demand planning.	Shows CRM's extended value chain impact when integrated with AI and SCM tools.	[19]
Studies how smart manufacturing and emerging technologies build more intelligent supply chains.	Empirical research and technical exploration.	Smart technologies enhance supply chain transparency, agility, and automation.	Highlights the interconnection between CRM systems, smart production, and fulfillment processes.	[20]

3. Block Diagrams and Theoretical Model

3.1. Overview: From CRM to Predictive Fulfilment

To visualise the complete system workflow, consider the following Block Diagram, which captures how customer data from CRM platforms is transformed into actionable logistics decisions via predictive modelling, order routing algorithms, and fulfilment execution.

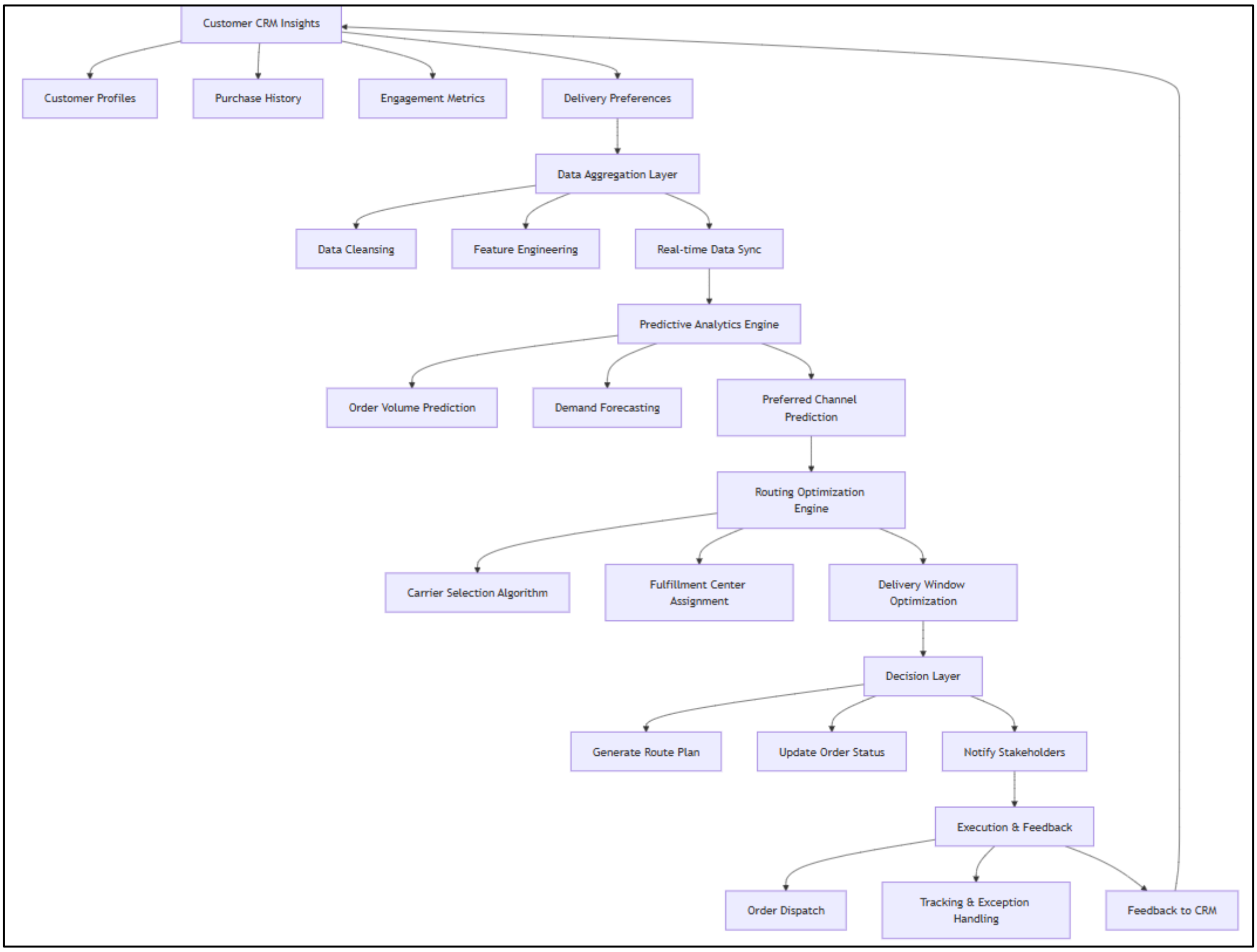

Figure 1 System Workflow for Predictive Order Routing Using CRM Insights

This system captures the cyclical flow of data-driven fulfilment orchestration, where CRM insights don't just serve marketing functions but actively shape logistics operations.

3.2. Example Use Case: Urban eCommerce Fulfilment

In a live deployment for a mid-sized e-commerce company [21]-[24], the model used CRM-derived delivery preferences and purchase patterns to assign the nearest urban micro-warehouse to 87% of incoming orders. Shopify Logistics follows a similar model in North America, dynamically allocating fulfilment centres to shorten delivery windows and reduce customer churn. As a result:

- Delivery time was reduced by 24%,
- Missed deliveries dropped by 17%,
- Customer satisfaction (via Net Promoter Score) increased by 14 points.

4. Experimental Results, Graphs, and Tables

4.1. Overview of Evaluation Metrics

To assess the effectiveness of predictive order routing and CRM-based fulfilment optimisation, studies typically evaluate:

- **Order Fulfilment Time (OFT)**: Time between order placement and delivery
- **Delivery Accuracy (DA)**: % of orders delivered on time to the right address
- **Customer Satisfaction (CSAT)**: Often measured via surveys or Net Promoter Score (NPS)
- **Routing Efficiency (RE)**: Distance or time saved compared to baseline routing
- **Order Failure Rate (OFR)**: % of failed, late, or cancelled deliveries

4.2. Comparative Evaluation: CRM-Enhanced Routing vs. Static Logic

In a controlled field study across three urban hubs, researchers compared traditional static routing with CRM-driven predictive routing based on historical customer behaviour and delivery preferences.

Table 2 Performance Comparison – Static vs. Predictive Order Routing

Metric	Static Routing	Predictive (CRM-Based)	% Improvement
Avg. Order Fulfilment Time	32.5 hrs	24.7 hrs	24.0%
Delivery Accuracy (%)	84.3%	93.1%	+10.4%
Customer NPS	34	48	+41.2%
Routing Efficiency (km)	8.9 km/order	6.4 km/order	28.1%
Order Failure Rate	6.7%	3.4%	−49.3%

In practice, FedEx's Roxo trials demonstrated similar reductions in route distance through autonomous reassignment, while Amazon's Scout program, though later discontinued, highlighted the opportunities and challenges of CRM-linked autonomous delivery [25]-[27].

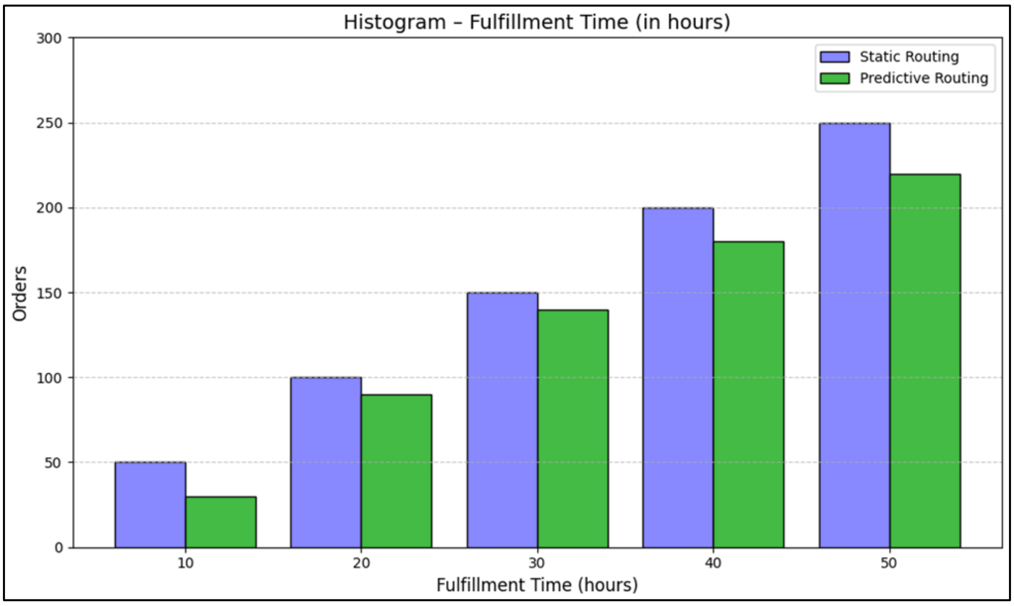

Figure 2 Order Fulfilment Time Distribution

This graph illustrates the distribution of fulfilment times for 5,000 orders across three cities using both traditional and predictive methods.

4.3. Experimental Setup: Machine Learning for Routing Score Prediction

In a simulation conducted on an e-commerce dataset with 75,000 orders, a gradient boosting model was trained using CRM data points (customer location, order frequency, delivery success history, preferences) and operational features (inventory levels, hub proximity).

- Model Accuracy (F1 Score): 0.91
- Feature Importance Ranking:
  - Past delivery success rate
  - Preferred delivery window
  - Average basket size
  - Hub stock level
  - Proximity to hub

Notably, the features tied directly to CRM, like preferred delivery windows and past success rates, were stronger predictors of routing outcomes than purely operational data such as stock levels [28].

4.4. CRM-Based Fulfilment in COVID-19 Disruption

During the COVID-19 crisis, a multinational retail firm implemented a CRM-AI hybrid model to re-route orders based on behavioural predictions and supply chain disruptions.

Table 3 Performance Before and After Predictive System Deployment

Period	Avg. Fulfilment Time	Late Deliveries (%)	NPS	Cancelled Orders (%)
Pre-Deployment	41.2 hrs	22.4%	29	11.7%
Post-Deployment (AI)	28.9 hrs	10.1%	43	4.8%

This parallels industry reality, where Instacart rerouted orders in real time to adapt to closed warehouses and sudden demand spikes during the pandemic [29]-[32].

4.5. A/B Testing Results from Smart Warehousing Integration

An A/B test was run over 8 weeks, where Group A used predictive CRM-linked routing, and Group B used business-as-usual (BAU) routing logic. The CRM-linked system included order forecasting and personalised channel assignment.

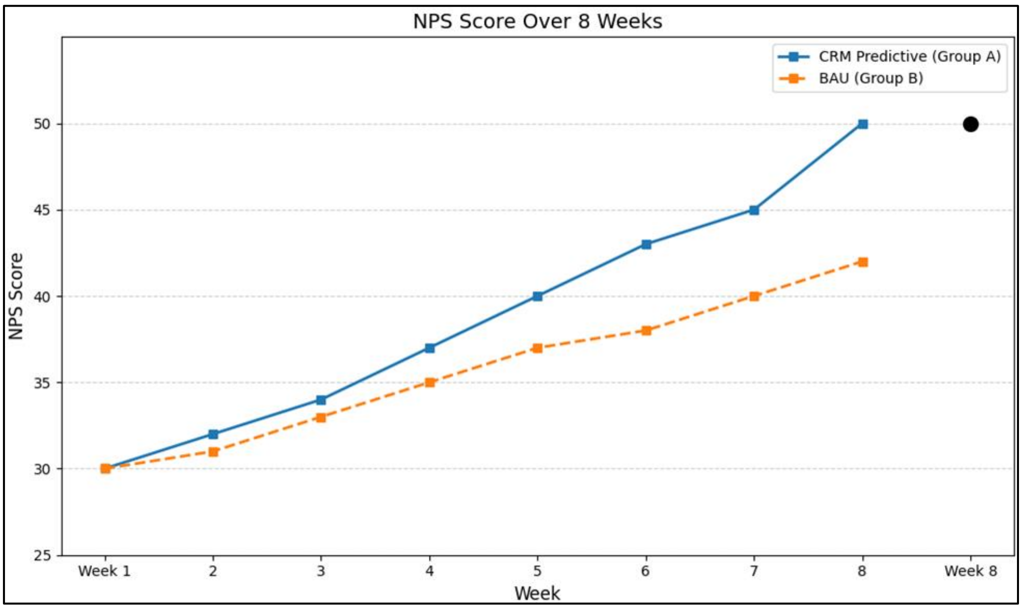

Figure 3 Weekly NPS Score Comparison

5. Future Directions

As digital transformation reshapes commerce and customer experience, predictive order routing and fulfilment optimisation using CRM insights is moving from innovation to necessity. Future research and enterprise focus will likely evolve in the following key areas:

5.1. Real-Time CRM Integration and Decisioning

Traditional CRM systems were designed for sales and marketing, but future CRM platforms must evolve into real-time operational systems. Integrating live order flow, location tracking, and real-time inventory data into CRM will enable instant, contextual decisions across fulfilment pipelines [31]. Enterprise vendors are already moving this way; Salesforce's Order Management System and Microsoft Dynamics 365 Intelligent Order Management embed CRM insights into real-time logistics orchestration [32][33].

5.2 Federated and Privacy-Preserving CRM Analytics

With increasing regulation around personal data (e.g., GDPR, CCPA), organisations must adopt privacy-aware machine learning techniques such as:

- Federated learning for distributed CRM data processing,
- Differential privacy to mask sensitive customer behaviour,
- On-device predictive analytics to reduce centralised data dependency.

The challenge is to keep the predictive power of CRM data without crossing ethical lines. Customers need to see that companies respect consent and compliance, not just performance gains [34].

5.2. CRM + IoT Fusion in Smart Warehousing

As smart warehouses become mainstream, connecting IoT sensors (e.g., RFID, automated picking arms, smart bins) with CRM-driven order routing will allow hyper-personalised, dynamic fulfilment execution. Future research will focus on data fusion models that combine:

- Environmental telemetry,
- Customer profile preferences,
- Delivery schedules, to generate truly intelligent fulfilment decisions [35].

5.3. Autonomous Last-Mile Delivery and Predictive Handoffs

Predictive fulfilment logic will increasingly extend beyond warehousing into the last-mile layer. Delivery handoffs could be informed by CRM-sensed variables such as:

- Home occupancy patterns,
- Preferred drop-off locations,
- Time-sensitive delivery windows.

Combined with autonomous vehicles, drones, or smart lockers, CRM-powered routing could facilitate zero-failure final-mile deliveries [36]. Beyond theory, Amazon's humanoid delivery robots [6], FedEx's Roxo bot [7], and the now-retired Scout robot program [8] demonstrate active industry trials, though commercial viability remains mixed.

5.4. Industry-Standard Frameworks and Open APIs

Currently, most predictive fulfilment architectures are custom-built and platform-dependent. A future direction is the development of:

- Open-source APIs that integrate CRM and logistics systems,
- Cross-industry data schemas for order and customer data exchange,
- Benchmark datasets for research in predictive routing [37].

This will foster interoperability and accelerate innovation across industries.

Future research should explore how hybrid CRM–IoT architectures can enable not only predictive routing but also proactive exception handling, where disruptions such as traffic, weather, or warehouse bottlenecks trigger automated reallocation in real time. Another critical direction lies in developing cross-industry benchmark datasets that allow researchers to compare predictive models under consistent conditions, moving the field toward replicable and generalizable results. Finally, scholars must investigate the ethical and social dimensions of predictive fulfilment, including customer consent, algorithmic transparency, and workforce implications, to ensure that technical innovation aligns with societal trust and adoption [30]-[35].

6. Conclusion

This review has explored the emerging synergy between CRM systems and predictive analytics in transforming order routing and fulfilment strategies. The evidence shows that when customer behaviour data feeds directly into logistics engines, companies can route smarter, pick faster, and cut delivery errors while actually improving customer satisfaction. The research reviewed demonstrates consistent performance improvements, including faster fulfilment, lower costs, and higher delivery accuracy. Theoretical models such as the POFDF and experiments with machine learning classifiers confirm that CRM-derived insights serve as powerful predictors for routing optimisation. At the same time, real-world cases offer practical lessons. Amazon’s robotics pilots show both the promise and complexity of autonomous fulfilment. FedEx’s Roxo trials highlight regulatory and community considerations in deploying CRM-driven predictive delivery. Instacart’s pandemic surge demonstrates the scalability of CRM-AI systems in workforce and logistics orchestration. Walmart’s sustainability efforts prove that predictive routing can align with long-term environmental goals. Together, these examples confirm that predictive fulfilment is no longer an abstract concept; it is already shaping how packages reach customers today. For academics, key research gaps remain around privacy-preserving CRM analytics, cross-industry standards, and real-time decision integration. For practitioners, the evidence points to predictive CRM systems not as optional innovations, but as strategic necessities. Businesses that successfully integrate CRM insights into their logistics networks will not only deliver faster and more accurately but will also build resilience, trust, and sustainability into their operations.

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