Supply Chain Insider
Volume 14, Issue 01, 65-88. 10-10-24
Article Received: 20-08-2024
Accepted: 15-09-2024
Available Online: 10-10-2024
ISSN: 2617-7420 (Print), 2617-7420 (Online)
DOI: 10.5281/zenodo.13865897
supplychaininsider.org

Leveraging AI to Overcome Key Challenges in Last-Mile Delivery: Enhancing Customer Experience and Operational Efficiency in E-commerce

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Abstract

This study explores the potential of leveraging Artificial Intelligence (AI) to address key challenges in last-mile delivery (LMD) within the e-commerce sector, with a focus on enhancing customer experience and operational efficiency. The research investigates the primary obstacles in LMD, such as high delivery costs, delays, and package handling issues, which contribute to customer dissatisfaction and operational inefficiencies. Utilizing a cross-sectional survey design, data were collected from 42 respondents, encompassing a diverse group of e-commerce users. The study examines the correlation between AI adoption and customer satisfaction, revealing a weak negative relationship, suggesting that factors beyond customer satisfaction, such as perceived operational efficiency and environmental impact awareness, may significantly influence AI adoption decisions. Key findings indicate that while customer satisfaction does not strongly predict AI adoption, there is a notable positive correlation between AI awareness, environmental impact awareness, and the intention to adopt AI-driven LMD solutions. The study highlights the importance of enhancing consumer understanding of AI's benefits and promoting sustainable delivery practices to increase AI adoption. Multiple AI solutions can address real-time last-mile delivery issues which can assist firms to design a more sustainable & customer-centric supply chain. Future research should focus on exploring additional determinants of AI adoption and the integration of AI with sustainable initiatives to further improve LMD services in e-commerce.

Keywords: *Artificial Intelligence (AI), Last-Mile Delivery (LMD), E-commerce, Customer Satisfaction, Operational Efficiency*

Introduction

The term "last mile" was originally used in telecommunications to describe the final leg of a telecommunication network. In the context of the supply chain of goods, Last-Mile Delivery (LMD) refers to "the last stage of the supply chain" (Bosona, 2020). LMD is fraught with unique challenges, including inefficiencies, high costs, security risks, and environmental concerns. For instance, LMD often involves complex logistics, such as vehicle routing problems (VRP), where optimizing routes to meet delivery windows while minimizing costs is paramount (Boyer & Prud'homme, n.d.). In the rapidly evolving landscape of (AI), generative AI provides a frontier of innovation and potential.

It can create new, previously unseen content, AI technologies have sparked a wave of interest across various sectors including e-commerce, promising to redefine the boundaries of creativity, efficiency, and problem-solving. (Yafei et al., 2024)

The rapid development of Internet technology and the acceleration of digital transformation have accelerated the pace of digital transformation, and e-commerce is ushering in an unprecedented era of opportunities and challenges (Liu, 2024). E-commerce has changed the retail industry, transforming how consumers receive goods and receive goods. Moreover, e-commerce has intensified the demand for faster, more reliable deliveries, straining existing infrastructure and operational capabilities (Schultz, 2024). Nowadays, Key logistics operations are identified as critical for e-commerce success, with customer satisfaction closely linked to delivery charges and times, necessitating innovative distribution channels to improve service. (Zabed et al., n.d.)

However, the challenges of LMD present a significant impact on customer satisfaction and operational efficiency in the e-commerce sector. As e-commerce continues to grow, particularly within highly populated metropolitan regions such as Dhaka City, the necessity for efficient, dependable, and customer-centric last-mile delivery solutions has grown progressively paramount. AI evolves as a paradigm-shifting force, creating new market opportunities, redefining traditional operations, and challenging existing business models. (Adel & Mohamed, 2023). This paper aims to explore the profound impact of artificial intelligence on the e-commerce sector, focusing on its capabilities, solving LMD problems, and its transformative effect on customer satisfaction and operational efficiency.

1.1 *Problem Statement*

Last-mile delivery represents the most complex and costly segment of the logistics chain, with challenges that range from high delivery charges and product safety concerns to communication gaps between retailers and customers. These issues hinder both operational efficiency and contribute to significant customer dissatisfaction, leading to increased competition in the market and customer churn within the e-commerce sector. Studies have shown that inappropriate delivery charges and concerns over data security and product safety during transit are major sources of frustration for customers, often resulting in a loss of trust and loyalty towards e-commerce platforms (Saha et al., 2023). Furthermore, the dynamic nature of customer demands in e-commerce necessitates a scalable and flexible delivery infrastructure, which is often lacking in traditional logistics models (Haque et al., n.d.). This gap underscores the need for innovative solutions that can effectively streamline last-mile delivery processes while addressing the critical pain points faced by customers.

1.2 *Research Objectives & Research Questions*

This research aims to analyze customer satisfaction and operational efficiency by solving the challenges of LMD using AI. Specifically, this research aims to:

I. Identify and analyze the primary challenges in last-mile delivery that contribute to customer dissatisfaction and inefficiency within the e-commerce sector.

II. Evaluate the potential of AI addressing the challenges of LMD, focusing on their ability to improve delivery reliability, security, and overall customer satisfaction.

RQ1: Which last-mile delivery (LMD) problem do customers face the most?

RQ2: How does the implementation of AI technologies impact customer satisfaction in last-mile delivery for e-commerce?

RQ3: What is the perceived effectiveness of AI in enhancing the operational efficiency of last-mile delivery services?

RQ4: How aware are e-commerce customers of AI technologies in last-mile delivery, and in what manner does this cognizance influence their interpretation of service excellence?

1.3 *Scope of the study*

The scope encompasses the analysis of current delivery practices, customer expectations, and the operational inefficiencies that hinder the effectiveness of last-mile delivery. By examining the intersection of logistics and technology, this study focuses on providing actionable insights for e-commerce platforms and delivery service providers to increase their customer service strategies and operational models. The study will also be focused on the effects of AI developments on the e-commerce sector, taking regulatory compliance, data security, and scalability into account. In summary, the research seeks to contribute to the ongoing discourse on optimizing last-mile delivery in e-commerce by demonstrating how AI can serve as a tool for overcoming existing challenges and making a more customer-centric and efficient delivery ecosystem.

2. Literature Review

2.1 *Introduction to Last-Mile Delivery (LMD) in E-commerce:*

LMD has emerged as a complex and critical component of the e-commerce supply chain, where packages are transported from distribution centers to the end customers. Nowadays, LMD is driven by the rapid growth of online shopping and the rising expectations of end customers for reliable, fast, and efficient delivery services. (Both Vrhovac et al., 2023) and (Wang et al., 2021) emphasize that LMD represents the most challenging and costly part of the logistics process, accounting for a significant portion of transportation expenses, particularly in urbanized areas with diverse customer requirements. This stage of delivery directly impacts customer satisfaction and loyalty, with factors such as delivery accuracy, speed, and transparency playing a crucial role in shaping consumer satisfaction. Moreover, the evolving market dynamics, particularly in regions like Vietnam, highlight the competitive landscape and the importance of sustainability in LMD operations. The heightened consciousness regarding ecological matters has precipitated the emergence of sustainable consumption, which underscores sustainable methodologies that yield a diminished adverse effect on the environment (Chowdhury et al., 2023). As consumer preferences shift towards faster, more convenient, and eco-friendly delivery options, companies must continually adapt to meet these demands while maintaining operational efficiency and sustainability. The convergence of these factors underscores the need for ongoing research and innovation in LMD to address the challenges posed by the growing volume of e-commerce orders and the complex logistics environment (C. N. Wang et al., 2021)

Challenges in Last-Mile Delivery: Addressing Efficiency, Cost, and Sustainability

The complexity of LMD provides so many challenges nowadays. Each of these challenges according to scholarly studies has been listed below:

1. **Social costs:** Such as traffic accidents, congestion and stress, and mobility barriers (possibility of absence of a car or not being able to drive) (Bosona, 2020)

2. **Nonsynchronous problem:** The time customers receive parcels is often nonsynchronous with that of couriers delivering the parcels, thereby resulting in high secondary delivery costs in the last mile delivery. Last-mile delivery has become a bottleneck restricting the development of the online shopping economy (Deutsch and Golany, 2018, Bergmann et al., 2020). To solve this contradiction, a facility called parcel locker (PL) has emerged in the last mile delivery. (Jiang, 2022)

3. **Urban Congestion:** The intricate urban environment, characterized by rampant congestion, severely restricts parking options and limits accessibility. This congestion complicates the delivery process, making it difficult for delivery vehicles to navigate through busy streets. (A Hai et al., 2023)

4. **Security problem for unattended delivery:** the possibility that packages left at a recipient's place without someone there to accept them will be stolen, damaged, or tampered with. (McKinnon & Tallam, 2003)

5. **High cost in low customer density:** This graph represents a very rough estimate of the relationship between population density and delivery cost. The current paper provides a simulation of the analysis of two independent factors on delivery costs. The first factor, customer density, is expected to negatively correlate with costs; i.e., delivery in areas with higher customer density should be less expensive. Extant research on the exact shape of this relationship is not available. The second factor, delivery window size, is expected to negatively correlate with costs; i.e., longer customer windows correspond with lower delivery costs. (Boyer & Prud'homme, n.d.)

6. **Vehicle routing problem (VRP):** In last-mile delivery, the Vehicle Routing Problem (VRP) entails maximizing a fleet of vehicles' routes to transport goods to several destinations as efficiently as possible. The objective is to reduce the overall trip time, distance travelled, and expenses while adhering to delivery window restrictions, truck capacity, and customer specifications. A successful VRP in the supply chain guarantees on-time delivery, lowers operating expenses, and raises customer satisfaction. (Boyer & Prud'homme, n.d.)

7. **CSP / CDP:** Deciding which customers to visit directly and which to cover via nearby facilities involves complex trade-offs and optimization. This study proposes a generalisation of the covering salesman problem (CSP), called covering delivery problem (CDP), which arises from the last mile delivery practice.CSP is a generalization of the TSP in which we have to satisfy all the customers' demands by visiting or covering them. The goal of the CSP is to construct a minimum length tour over a subset of the given customers such that each customer, not visited on the tour, is within the covering distance of at least one visited customer (Shaelaie)

8. **The travelling salesman problem (TSP):** It entails determining the quickest path that enables a salesman to travel to every city precisely once and then return to the starting location. It poses the subsequent inquiry: Considering a compilation of distances and urban centers between every pair of cities, what constitutes the minimal feasible path that allows for the visitation of each city precisely one time while ultimately returning to the originating city? (Travelling salesman problem, n.d.)

9. **Facility Location Problem (FLP):** When distribution centres cannot be constructed at the same location at which the customer zones are located. The Facility Location Problem involves determining the optimal locations for facilities (such as distribution centres) to minimize the cost of serving a set of customer locations. (Shaelaie)

10. **The quota travelling salesman problem (QTSP):** is a generalization of the TSP in which the salesman has to visit a given quota of vertices while minimizing the total travel cost. In this problem, each vertex has a pre-determined amount of prize that could be collected by the salesperson by being visited on the tour. The k-TSP is a special case of the QTSP in which each vertex has one unit of the prize and the goal is to visit k vertices, to collect k units of the prize (Shaelaie)

11. **Increased demand for fast and efficient delivery:** The rising demand for efficient and fast deliveries places significant pressure on last-mile companies. Retailers need providers who can meet the increasing expectations for quick deliveries while ensuring consistency and reliability. (Schultz, 2024)

12. **Poor address quality:** A study found that 73% of consumers experience delivery failures. These failures can result from poor address quality and affect delivery profitability. For global brands and retailers, localizing the address field makes a significant and positive difference. Address formats vary from country to country. Localising the address fields in the checkout puts the shopper at ease and makes the address label easy to read for delivery personnel which reduces delivery failures. Retailers need localised checkouts and reliable providers who can effectively address and mitigate these issues. (Schultz, 2024)

13. **Inefficiencies in failed delivery:** Inefficiencies within the last mile delivery process, such as failed deliveries, return pickups and suboptimal route planning, contribute to higher overall distribution costs for retailers. Failed deliveries result in additional expenses. The financial repercussions of these inefficiencies underscore the critical need for streamlined and cost-effective last-mile solutions. (Schultz, 2024)

14.

15. **Environmental Impact:** Conventional delivery strategies, which often rely on motorbikes and cycle rickshaws, have proven to be agile but environmentally detrimental. This raises concerns about sustainability and the ecological footprint of last-mile delivery operations. (A Hai et al., 2023)

2.2 *The Role of Artificial Intelligence in Transforming Last-Mile Delivery*

Artificial Intelligence (AI) is increasingly offering powerful solutions to everyday challenges across various fields, including last-mile delivery (LMD). Within this domain, Generative Artificial Intelligence—a rapidly evolving subset of AI—has emerged as a key player. Technologies such as Generative Adversarial Networks (GANs) and Generative Pre-trained Transformers (GPT) are transforming business applications by automating content creation, enhancing customer interactions, and driving innovation. These AI advancements are critical in business contexts, as they augment human creativity, boost operational efficiency, and unlock new opportunities, helping enterprises maintain a competitive edge in the digital age (Reznikov, 2024).

One of the primary ways AI is reshaping last-mile delivery is through route optimization. By analyzing vast amounts of data, including traffic patterns, weather conditions, and delivery schedules, AI can determine the most efficient routes for delivery vehicles. This capability not only reduces delivery times and costs, as demonstrated by companies like Tesco, but also contributes to sustainability efforts by minimizing fuel consumption (Sorooshian et al., 2022).

Additionally, AI's impact extends beyond just route planning. Autonomous vehicles (AVs), while often in the spotlight, represent just one aspect of AI's potential in transportation. AI also addresses broader issues related to safety, reliability, predictability, efficiency, and sustainability in the transport sector (Conde & Twinn, n.d.).

AI's real-time data analysis capabilities further enhance last-mile delivery by allowing companies like Walmart and DHL to monitor and adjust their strategies dynamically. This adaptability ensures timely deliveries and boosts customer satisfaction (Hoffmann & Prause, 2018). Moreover, AI helps companies navigate complex regulatory landscapes by analyzing local laws and ensuring compliance with legal requirements, facilitating smoother operations across different regions (Sorooshian et al., 2022). Cost reduction is another significant benefit, with AI optimizing routes, reducing failed deliveries, and minimizing congestion, thus lowering operational costs while maintaining competitive pricing and service quality.

In the realm of e-logistics, AI plays a crucial role by matching shippers with delivery service providers, streamlining the last-mile delivery process, and ensuring efficient resource allocation (Sorooshian et al., 2022). Furthermore, AI enhances safety and reliability in last-mile delivery. Companies adopting Edge Intelligence (EI) technologies report improved service reliability, with better route planning and real-time adjustments leading to on-time deliveries and increased customer satisfaction (Mendes dos Reis, 2024). By reducing human error and optimizing delivery routes, AI also mitigates transport-related risks, which is especially important in congested urban environments (Sorooshian et al., 2022).

AI's contribution to last-mile delivery extends to improving delivery time forecasting, which is essential for meeting customer expectations in today's fast-paced logistics environment (Rosendorff & Fabian, n.d.). Additionally, AI addresses urban logistics challenges by optimizing delivery routes, reducing congestion, and minimizing environmental impacts, thereby enhancing the sustainability of urban logistics operations (Giuffrida et al., 2022). However, integrating AI into last-mile delivery is not without its challenges. The study by Rosendorff & Fabian (n.d.) underscores the importance of developing robust AI models that can seamlessly integrate with existing logistics systems to enhance real-time data processing, resource allocation, and overall delivery efficiency.

2.4 *Customer Satisfaction in E-commerce LMD*

Customer satisfaction in e-commerce last-mile delivery plays a critical role in the overall success of online shopping, influencing customer loyalty and brand reputation. As the final step in the logistics chain, last-mile delivery, which involves transferring packages from transport hubs to the end user, is a key touchpoint in the customer journey. The efficiency, reliability, and convenience of this stage significantly impact customer satisfaction (Mangiaracina et al., 2019). Studies have shown that inappropriate delivery charges and concerns over data security and product safety during transit are major sources of frustration for customers, often resulting in a loss of trust and loyalty towards e-commerce platforms (Saha et al., 2023). Furthermore, the dynamic nature of customer demands in e-commerce necessitates a flexible and scalable delivery infrastructure, which is often lacking in traditional logistics models. (Haque et al., n.d.)

In the context of e-commerce, various factors contribute to customer satisfaction. Delivery method and payment options, for instance, play crucial roles in different regions, with customer preferences varying based on local customs and infrastructure (Zabed et al., n.d.). The rise of innovative last-mile delivery solutions, such as Automated Parcel Stations (APS), is also transforming the landscape. APS allows consumers to self-collect parcels at their convenience, leading to higher first-time delivery success rates and reduced waiting times, thereby enhancing customer satisfaction (X. Wang et al., 2020).

Understanding critical beliefs and attitudes towards last-mile delivery services is essential for logistics operators aiming to improve service offerings. Factors such as on-time delivery, accuracy, and perceived service value are directly linked to the user experience, which in turn influences customer satisfaction (Vrhovac et al., 2023). Additionally, trust in courier services plays a pivotal role. Research shows that smooth delivery processes, convenience, and joyful anticipation are strongly associated with customer trust, which enhances the overall delivery experience (Vrhovac et al., 2023).

E-commerce platforms also contribute to customer satisfaction by providing better shipment tracking and more accurate information on expected delivery times, helping to mitigate frustrations related to delays. This capability enhances the efficiency of last-mile delivery and further contributes to customer satisfaction (Jiang et al., 2022). In conclusion, customer satisfaction in e-commerce last-mile delivery is influenced by a combination of delivery efficiency, service reliability, and the ability to meet customer expectations. Companies that prioritize optimizing these aspects are likely to gain a competitive advantage in the market.

2.5 Operational Efficiency in AI-driven LMD

Artificial intelligence (AI) is increasingly recognized for its transformative potential in enhancing operational efficiency in last-mile delivery (LMD). Last-mile delivery, a critical stage in the logistics process, often presents challenges such as high costs, inefficiencies, and environmental concerns. Research by (Sorooshian et al. 2022) discusses how AI technologies, including machine learning and real-time data analysis, can optimize routes and improve decision-making in LMD. These advancements contribute significantly to operational efficiency, particularly through the use of autonomous vehicles and drones, which are designed to navigate urban environments more cost-effectively and with a lower environmental impact. Some applications of AI bringing efficiency are-

Streamlining Operations: AI-based technologies simplify various last-mile delivery activities. They help streamline operations by automating processes, leading to faster delivery times and improved customer satisfaction. This efficiency is crucial as customer demands for quicker deliveries continue to rise. (Jucha, 2021)

Data Utilization: AI allows for the creation of data sets that help control patterns and phenomena in delivery logistics. By employing predictive analytics, AI can analyze historical trends and predict future patterns, which aids in better decision-making regarding delivery routes and resource allocation. (Jucha, 2021)

Job Displacement Concerns: While AI enhances operational efficiency, it also raises concerns about job displacement. The automation of tasks traditionally performed by humans poses a threat to employment in the logistics sector. The paper discusses the balance between leveraging AI for efficiency and the potential impact on the workforce. (Jucha, 2021)

Operational Framework: The proposed information systems architecture by (Rosendorff & Fabian, n.d.) aims to embed AI-driven solutions into existing logistics operations. This architecture facilitates real-time data processing and communication, allowing for better resource allocation and improved customer satisfaction through timely notifications and updates.

Production efficiency: Recent technological advancements, such as cloud computing, big data, and improved machine learning algorithms, are accelerating the mainstreaming of AI in production environments. The Annual Manufacturing Report of 2018 indicates a strong belief among senior manufacturing executives that AI and other "Smart Factory" technologies will significantly boost productivity and enable smarter working conditions. (Gordon, 2018)

Impact of E-commerce Growth: The rise in e-commerce has heightened the importance of optimizing last-mile logistics. AI technologies are essential in addressing the challenges posed by increased consumer expectations for customized delivery experiences and the need for efficient supply chain management. (Giuffrida et al., 2022)

2.6 Gaps in the Literature and Future Research Directions

Despite the significant advancements in AI-driven last-mile delivery, several gaps remain in the literature. One major gap is the need for empirical studies that examine the long-term impacts of AI integration on operational efficiency and customer satisfaction. While the existing research provides valuable insights into the potential benefits of AI in LMD, there is a lack of comprehensive studies that evaluate these technologies' performance over extended periods.

Another area that requires further exploration is the ethical implications of AI adoption in last-mile delivery. Issues such as data privacy, job displacement, and the environmental impact of autonomous vehicles and drones are critical concerns that need to be addressed (Demir et al., 2022). Future research should focus on developing ethical guidelines for AI implementation in logistics and exploring ways to mitigate the potential negative impacts on the workforce and the environment.

Lastly, there is a need for research that explores the scalability of AI-driven solutions in different geographical contexts, particularly in emerging markets where logistics infrastructure may be less developed (Sorooshian et al., 2022). Understanding how AI can be adapted to varying market conditions will be crucial in driving the global adoption of these technologies and ensuring their sustainability in the long term.

3. Methodology

This study employed a cross-sectional survey design to explore the potential of AI in addressing last-mile delivery challenges in e-commerce. The methodology was chosen to capture diverse perspectives from participants across different demographics, ensuring a comprehensive understanding of the research problem.

3.1 Participants

The participants for this study comprised 42 respondents, selected using a convenience sampling method. The sample included a diverse group of individuals encompassing students, entrepreneurs, and working professionals, reflecting the diverse e-commerce user base. The diversity in respondents ensured a broad spectrum of insights, which are crucial for understanding various perspectives on AI-driven last-mile delivery in the e-commerce sector. The participants' demographics were captured in the first section of the survey, which sought to understand their primary role, frequency of e-commerce usage, and the types of products they typically purchased.

3.2 Study Design

This study adopted a cross-sectional survey design to investigate the potential of generative AI in overcoming key challenges associated with last-mile delivery in e-commerce. The survey was structured into six distinct sections, each focusing on different aspects of the research objective. The design aimed to capture the participants' perceptions, attitudes, and expectations regarding the application of AI in last-mile delivery, as well as their awareness of the environmental impact and operational efficiency.

3.3 Materials

The primary material used in this research was a structured Google Forms questionnaire, which included both closed and open-ended questions. The questionnaire consisted of 17 closed-ended questions, and 1 open-ended questions to gather qualitative insights. The questionnaire was designed to be comprehensive and user-friendly, ensuring that participants could easily provide their responses. The questions were divided into six sections, each targeting a specific variable identified as crucial for the study. These sections included demographic information, current last-mile delivery challenges, customer perceptions of AI, potential AI applications in last-mile delivery, operational efficiency with AI, and future expectations.

To ensure clarity and relevance, the questionnaire was pre-tested with a small group of 3 respondents who were similar to the study's target population. This pre-testing phase allowed the researchers to identify and rectify any ambiguities or issues in the questions, thereby enhancing the overall validity and reliability of the survey instrument before full-scale distribution.

3.4 Procedure

The research procedure began with the development of the questionnaire, which was crafted based on the research objectives and variables. After finalizing the questionnaire, it was distributed through various social media platforms, including WhatsApp, Facebook, and Messenger, to reach a wide audience. Participants were informed about the purpose of the research and were assured of the confidentiality and anonymity of their responses. They were also given the freedom to skip some questions they were not comfortable answering such as the open-ended question we included in the questionnaire.

3.5 *Sampling*

Convenience sampling was employed to select participants for the study. This non-probability sampling method was chosen due to its practicality and efficiency in reaching a large number of respondents quickly. Although convenience sampling has limitations in terms of generalizability, it was deemed appropriate for this exploratory study, which aimed to gather initial insights into the perceptions and attitudes toward AI in last-mile delivery.

3.6 *Data Collection Process*

Data collection was conducted entirely online using the Google Forms platform. The survey link was disseminated across social media networks, allowing for easy access and participation. The online format facilitated a swift and efficient data collection process, ensuring that responses could be gathered in real-time. The survey was kept open for a specified period, during which a total of 42 responses were collected. The responses were automatically recorded in Google Sheets, which allowed for straightforward data management and analysis.

3.7 *Measures*

The data collection process utilized both quantitative and qualitative measures. The closed-ended questions were designed to capture quantitative data on participants' perceptions, attitudes, and behaviors related to AI-driven last-mile delivery. 5-Point likert scales were commonly used to measure the intensity of these perceptions. On the other hand, open-ended question provided qualitative insights, allowing participants to elaborate on their views and suggestions. These qualitative responses were crucial for understanding the nuances of customer satisfaction, AI adoption intention, and environmental impact awareness in their future usage. The combination of both types of data ensured a comprehensive analysis of the research questions.

3.8 *Limitations of the Methodology*

While the methodology employed in this study provided valuable insights into the potential of generative AI in enhancing last-mile delivery in e-commerce, there are several limitations that should be acknowledged.

Firstly, the study utilized a convenience sampling method, which, while practical and efficient, may limit the generalizability of the findings. The sample consisted of 42 respondents, who were primarily accessible through the researcher's social media networks. This sampling technique could introduce a bias, as it may not accurately represent the broader population of e-commerce users, particularly those who are less active on social media or those from different geographic or socio-economic backgrounds.

Secondly, the relatively small sample size (n=42) could also be a limiting factor. With a larger and more diverse sample, the study might have captured a wider range of perspectives and yielded more statistically robust conclusions. The small sample size may have also limited the ability to detect subtle differences in perceptions and attitudes toward AI-driven last-mile delivery.

Moreover, the cross-sectional design of the study only captures participants' perceptions at a single point in time. This design does not account for changes in attitudes or behaviors over time, which could be particularly relevant in a rapidly evolving field like AI in e-commerce.

Lastly, while the questionnaire included both closed and open-ended questions to gather qualitative insights, the depth of qualitative data may be limited. Open-ended responses, while useful, may not provide the richness of data that could be obtained through more in-depth qualitative methods such as interviews or focus groups. These methods could have provided a deeper understanding of the underlying reasons behind participants' perceptions and attitudes toward AI in last-mile delivery.

In conclusion, this methodology was designed to align with the research objectives and hypotheses, ensuring that the data collected was relevant and robust enough to provide meaningful insights into the potential of AI in enhancing last-mile delivery efficiency and customer experience in the e-commerce sector.

4. Data Analysis and Findings

4.1 *Model Variables and Hypotheses Overview*

In this section, the relationship between the identified variables and the research hypotheses is visually represented in the diagram provided below. The model comprises six key variables: Customer Satisfaction (V1), Environmental Impact Awareness (V2), AI Awareness and Perception (V3), Perceived LMD Efficiency (V4), Operational Efficiency with AI (V5), and AI Adoption Intention (V6). These variables are organized into two distinct hypotheses, reflecting their respective roles in the study.

Hypothesis 1 (H1) contains a positive correlation between the use of AI technologies in last-mile delivery (LMD) and customer satisfaction with e-commerce services. This hypothesis is supported by Variable 1 (V1) and Variable 6 (V6), which directly influence each other within the model, illustrating the anticipated impact of AI adoption on customer satisfaction.

Hypothesis 2 (H2), on the other hand, reflects the influence of perceived operational efficiency of AI-driven LMD services on the intention to adopt AI in e-commerce platforms. This hypothesis is connected through Variables 2 (V2), 3 (V3), 4 (V4), and 5 (V5). These variables interact to demonstrate how environmental awareness, AI perception, and perceived efficiency contribute to operational efficiency and ultimately influence AI adoption.

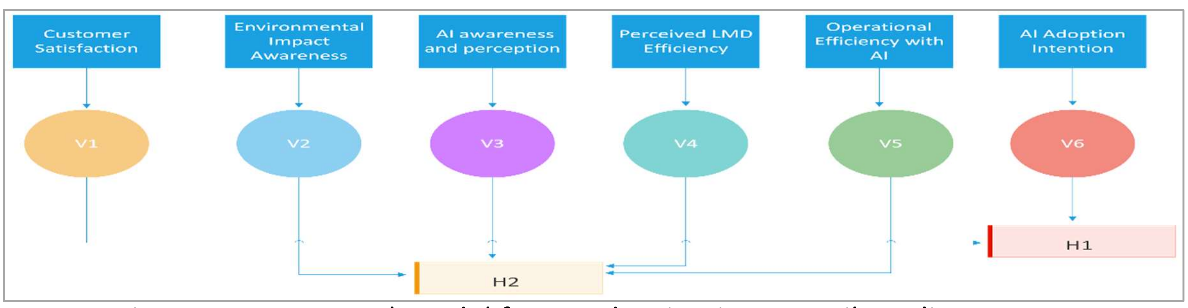

Figure 1. Conceptual Model for AI Adoption in Last-Mile Delivery: Factors Influencing Customer Satisfaction and Operational Efficiency

4.2 *Descriptive Statistics*

Here the key findings from the analysis of six variables (V1 to V6) that provide insights into the distribution and central tendencies of the data. The mean values across the variables suggest a generally positive inclination towards the aspects being measured. For instance, V2 (Environmental Impact Awareness) has the highest mean value of 3.5238, indicating that respondents are relatively more aware of environmental impacts, whereas V1 (Customer Satisfaction) has a lower mean of 2.7619, reflecting more variability in satisfaction levels among the participants.

The standard deviations range from 0.54740 to 1.10956, highlighting that while some variables like V1 and V6 (AI Adoption Intention) are more consistent, others like V2 show greater variability in responses. The skewness and kurtosis values are close to zero for most variables, indicating that the data is fairly normally distributed. However, V3 (AI Awareness and Perception) shows a higher negative skewness of -1.196, suggesting that a larger proportion of respondents have lower levels of AI awareness and perception.

Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation	kewness	kewness	Kurtosis	Kurtosis
	Statistic	Statistic	Statistic	Statistic	Statistic	tatistic	Std. Error	Statistic	d. Erro
	4	1.3	3.(	2.761	.5474	-.34	55	14	17
	4	1.(	5.(	3.523	1.1095	-.96	55	56	17
	4	1.(	4.(	3.404	.7669	-1.19	55	033	17
	4	2.(	5.(	3.809	.7152	-.38	55	52	17
	4	2.(	5.(	3.785	.8420	-.08	55	90	17
	4	2.6	4.6	3.769	.5533	-.15	55	97	17
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Table 1. Descriptive Statistics and Skewness/Kurtosis for Variables V1 to V6

4.3 *Consumer Preferences Across Product Categories*

The data reveals that a significant portion of customers frequently purchase from the Fashion and Lifestyle category, with 27 out of 42 respondents (64.3%) indicating this preference. This is followed closely by the Food and Beverages category, which 24 respondents (57.1%) often order from. Other categories like FMCG (Fast-Moving Consumer Goods) and Stationery also see some engagement, with 14.3% and 19% of respondents purchasing from these categories, respectively. Medicine, Skincare, and electronic items appear to be less common choices, each accounting for a smaller fraction of the total responses. This distribution highlights a strong consumer inclination towards fashion and lifestyle products, along with food and beverages, suggesting that these are the primary areas of focus for many online shoppers in the study sample.

4.4 *Prevalent Delivery Issues and Consumer Dissatisfaction*

When it comes to delivery issues, high delivery costs emerge as the most frequently reported problem, affecting 20 out of 42 respondents (47.6%). Delayed deliveries are another major concern, as noted by 17 respondents (40.5%). Issues related to package handling and quality are also significant, with 15 respondents (35.7%) citing them as frequent problems. The data further indicates that limited delivery coverage (21.4%) and unmatched delivery time/windows (26.2%) also contribute to delivery dissatisfaction. Interestingly, inconsistent or incorrect deliveries (9.5%) and poor communication/inadequate updates (16.7%) are reported less frequently, though they still pose notable challenges. Security reasons for unattended deliveries appear to be a non-issue in this dataset.

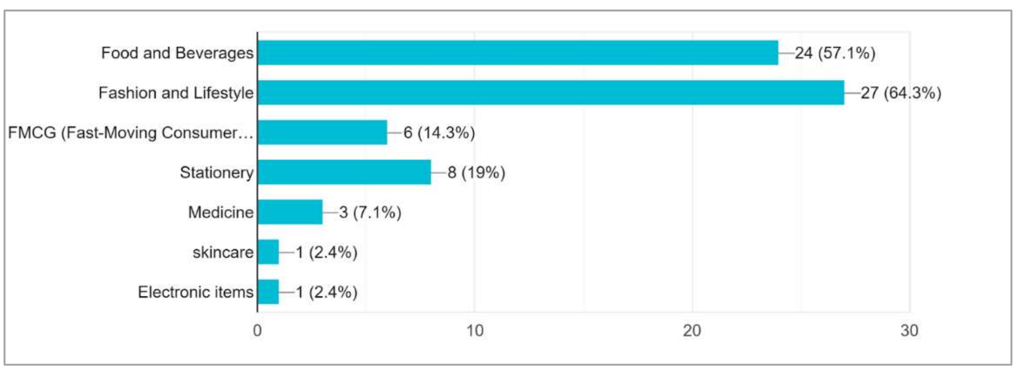

Figure 2. Distribution of Product Categories in Consumer Purchases

4.5 *Interpretation of Customer Purchase Behavior and Delivery Issues*

The data suggests that customers are predominantly engaging with the fashion and lifestyle segment, alongside food and beverages, which could be driving demand in these categories. However, the high cost of delivery and delays are primary obstacles that could be undermining customer satisfaction. Addressing these issues, particularly by optimizing delivery costs and improving timeliness, could enhance customer experience and potentially increase repeat purchases in these popular categories. The frequent complaints about package handling and quality also suggest a need for better logistical practices to ensure product safety and customer trust.

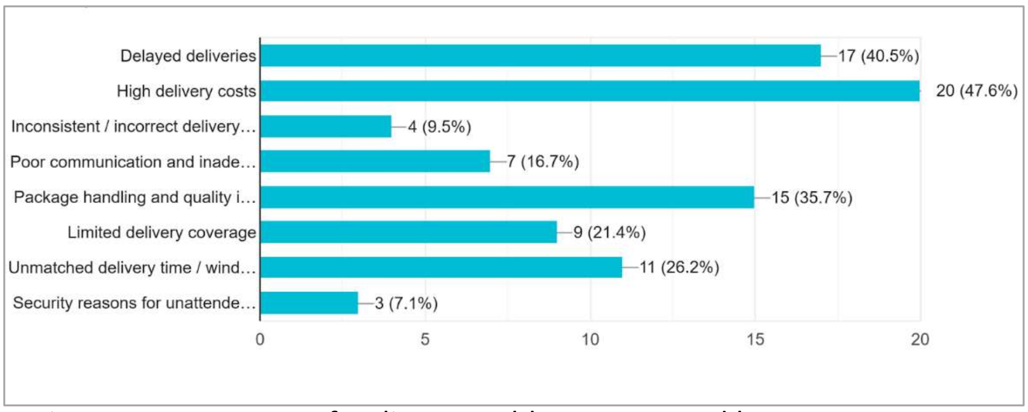

Figure 3. Frequency of Delivery Problems Reported by Customers

4.6 *Analysis and Interpretation of Hypotheses Testing*

4.6.1 H1: Customer Satisfaction and AI Adoption Intention

The table delineates the correlation findings between Variable 1 (V1: Customer Satisfaction) and Variable 6 (V6: AI Adoption Intention), which are intrinsically associated with Hypothesis 1 (H1). The Pearson correlation coefficient reveals a negative correlation of -0.114 between V1 and V6. This indicates a weak inverse relationship, suggesting that as customer satisfaction (V1) experiences a slight increase, the intention to adopt AI (V6) tends to decrease, albeit to a minimal extent.

Despite this finding, the correlation does not achieve statistical significance. The p-value associated with this correlation is 0.473, which exceeds the conventional alpha threshold of 0.05. This lack of statistical significance suggests that the observed correlation may be due to random variability rather than a substantive relationship between the variables. Consequently, the results imply insufficient evidence to support Hypothesis 1, indicating that customer satisfaction may not significantly influence the intention to adopt AI in last-mile delivery services.

rrelations		V6
arson Correlation		14
. (2-tailed)		73

Table 2. Correlation Matric Between Variables V1 and V6

4.6.2 H2: Operational Efficiency and AI Adoption Intention

To test Hypothesis 2 (H2), which posits that perceived operational efficiency of AI-driven last-mile delivery (LMD) services positively influences the intention to adopt AI in e-commerce platforms, we analyzed the correlation between Variables 2 (Environmental Impact Awareness), 3 (AI Awareness and Perception), 4 (Perceived LMD Efficiency), and 5 (Operational Efficiency with AI) with Variable 6 (AI Adoption Intention). The following correlations were observed:

- V2 (Environmental Impact Awareness) and V6: Pearson correlation = 0.400, p = 0.009. This indicates a moderate positive correlation that is statistically significant. It suggests that greater awareness of environmental impacts is associated with a higher intention to adopt AI technologies in e-commerce.

- V3 (AI Awareness and Perception) and V6: Pearson correlation = 0.503, p < 0.001. This reflects a strong positive correlation that is highly significant, implying that increased awareness and positive perception of AI are strongly linked to the willingness to adopt AI technologies.

- V4 (Perceived LMD Efficiency) and V6: Pearson correlation = 0.293, p = 0.060. This positive correlation is not statistically significant, indicating a trend where perceived efficiency is associated with a greater intention to adopt AI, but additional data might be needed for confirmation.

• V5 (Operational Efficiency with AI) and V6: Pearson correlation = 0.292, p = 0.060. Similar to V4, this positive correlation is not statistically significant, suggesting a trend that requires further investigation.

etails						
	arson Correlation		19**	06	23	00**
	g. (2-tailed)		001	91	37	09
	arson Correlation	19**		22	89	32
	g. (2-tailed)	001		43	75	70
	arson Correlation	06	22		17**	03**
	g. (2-tailed)	91	43		06	001
	arson Correlation	23	89	17**		93
	g. (2-tailed)	37	75	06		50
	arson Correlation	00**	32	03**	93	
	g. (2-tailed)	09	70	001	50	

Table 3. Correlation Matrix of Variables V2, V3, V4, V5, and V6

In conclusion, the results provide partial support for Hypothesis 2. Environmental impact awareness and AI awareness are significantly associated with AI adoption intentions. However, perceptions of operational efficiency, while positively associated with AI adoption intention, did not reach statistical significance. This indicates that other factors may also play crucial roles in the adoption decision process. The findings suggest that strategies to promote AI technologies in e-commerce should focus on enhancing visibility and perceived benefits, particularly in operational and environmental contexts.

4.7 *Discussion of Findings:*

The findings from this study offer a comprehensive view of the current state of last-mile delivery (LMD) services in Dhaka's e-commerce sector, with a particular focus on the potential role of AI technologies in enhancing both customer satisfaction and operational efficiency. The descriptive analysis highlights the variability in customer satisfaction, with relatively lower satisfaction levels suggesting a need for improvement in delivery services. On the other hand, the strong awareness of environmental impacts among consumers indicates a potential avenue for promoting more sustainable delivery practices.

Interestingly, the analysis of the correlation between customer satisfaction and AI adoption intention reveals an unexpected weak negative relationship, implying that increased satisfaction does not necessarily lead to a greater willingness to embrace AI-driven solutions. This finding suggests that other factors, such as the perceived efficiency and cost-effectiveness of AI, may play a more pivotal role in influencing adoption decisions.

The examination of customer purchase behavior and delivery issues further underscores the critical challenges faced by e-commerce platforms, particularly in terms of high delivery costs and delays, which are the most frequent complaints among customers. Addressing these issues will be crucial for improving customer satisfaction and fostering a more positive perception of AI in last-mile delivery.

5. Leveraging AI to address Last-Mile Delivery Issues:

As per the customer data collected for this study, multiple last mile delivery issues have been reported by the customers including high delivery costs, delayed deliveries, package handling and quality issues, unmatched delivery time/windows, limited delivery coverage etc. Leveraging AI to address LMD issues can improve organizational efficiency, reduce costs and increase customer satisfaction:

5.1 Route Optimization:

Route optimization assists companies to select the optimal route for a delivery analyzing real time traffic data, weather conditions, roadblocks, customer preference, type of deliverables and other necessary variables. This efficient way of route selection can reduce fuel consumption, delivery time and improve customer satisfaction. Reinforcement learning (RL), Genetic Algorithms (GA), Ant Colony Optimization (ACO) are some of the machine learning algorithms that can optimize routes based on real-time data.

5.2 Demand Prediction and Inventory Management:

Analyzing previous customer and organizational data, machine learning algorithms can predict demands which assists companies to cluster delivery locations and manage inventories. Relocation of delivery goods and services closer to high demanding delivery locations results in reduction of time, cost and travelled distance. Time Series Forecasting (such as, ARIMA), Regression Models including LASSO (Least absolute Shrinkage and Selection Operator) and Linear Regression, LSTM (Long Short-Term Memory Networks – all these algorithms are helpful for efficient demand prediction and time-series forecasting.

5.3 Dynamic Rerouting:

Dynamic rerouting is a much solution for densely populated locations with traffic congestion. As it can changes routes based on dynamic traffic data, issues related to emergency roadblocks or traffic jam can be efficiently handled. Algorithms like, dynamic programming g (DP), Markov Decision Processes (MDPs) calculate the shortest routes for different situations utilizing dynamic data.

5.4 Parcel Grouping and Consolidation:

Similar to customer segmentation, AI is also used in parcel grouping based on delivery locations, transportations mode, deliverables etc. which ultimately results in reduced delivery trips. K-Means Clustering is a much practiced algorithm for such clustering considering locations and distances. Moreover, hierarchical clustering works efficiently when it is about managing a number of destinations.

5.5 Sustainability and Green Delivery Initiatives:

Analyzing carbon footprints and following electric vehicle routing optimization, AI can map eco-friendly routes and this ensures minimum fuel consumption and emissions. Multi-Objective Optimization Algorithms, Linear Programming etc. contribute towards ensuring a more sustainable and eco-friendly last mile delivery.

Additionally, AI can make efficient management of driver and transportation modes, design and implement autonomous delivery solutions like, drones and robots, utilize data analytics and help in decision making, detect frauds and enhance security of deliverables. Implementing all these AI strategies can efficiently address last mile delivery issues which will ultimately create a solid foundation for a sustainable and dynamic supply chain operation.

6. Conclusion and Future Research Directions

The findings suggest that while AI has the potential to significantly improve last-mile delivery, its adoption is not solely dependent on customer satisfaction. The weak correlation between these variables indicates that future research should explore other determinants of AI adoption, such as cost, perceived benefits, and the ease of integration with existing systems. Moreover, given the high level of environmental awareness among consumers, future studies could investigate how sustainability initiatives, possibly supported by AI, influence customer loyalty and satisfaction in e-commerce. Additionally, further research is needed to delve into the reasons behind the negative skewness in AI awareness and perception, as increasing consumer understanding of AI's benefits could be key to its wider acceptance in the industry. By focusing on these areas, future studies can provide deeper insights into the strategic implementation of AI in last-mile delivery, ensuring it meets both operational goals and customer expectations.

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