BerkeleyMEng

**E295 Capstone Project Cover Sheet**

Team ID #: 164
Team Member Names: Ruoyu Liang, Michelle Lu, Minke Lu, Egill Agnar Oktosson
Subject Area: Logistics Data Analysis
Team Point-of-Contact: Ruoyu Liang
Team Point-of Contact email address: ruoyuliang@berkeley.edu

| Please note any exceptions, if any, to the default guidelines for your Capstone Project: |
|---|
| |

Does your project require an NDA: Y N

Is your Capstone team aiming to publish your Capstone Report: Y N

If yes, in which publication: ________________________________________

Is your Capstone team aiming to present your project at a conference: Y N

If yes, which conference and when is it: ________________________________

# Data-Driven Machine Learning Models for Enhancing E-commerce Customer Satisfaction

Project ID# 164

Ruoyu Liang, Michelle Lu, Minke Lu, Egill Agnar Oktosson
University of California, Berkeley
April 2024

# Table of Contents

## Executive Summary

[Author: MEL, EAO; Editor: EAO] Companies that provide e-commerce or online delivery services place great importance on customer satisfaction. When customers are satisfied, companies benefit from increased loyalty, improved brand image, and growth opportunities. Therefore, finding ways to improve customer satisfaction and reviews is critical to e-commerce businesses. This project aims to use machine learning and data analysis to drive data-driven decision-making for enhancing customer satisfaction. Machine learning techniques are used on order and delivery datasets from a large Chinese logistics company to draw insights into how different elements such as delivery timing can be leveraged to influence customer satisfaction.

By using machine learning to examine various attributes and conducting different types of timing analyses on the e-commerce dataset, we have successfully gained insights into how different parts of the delivery process, such as delivery timing and delivery promise speed, can impact customer satisfaction. Our process included utilizing existing research on logistic data analysis, and then building upon it to conduct additional analyses and draw further insights. For instance, one insight that emerged to improve customer satisfaction suggested that customers appreciate early notifications of delivery start actions. From the results of our analysis, we were able to observe a range of behaviors, both expected and unexpected, in how different variables or time periods affect customer satisfaction.

Any other headlines or stats to offer here? cf. p.10

Building upon the insights and methodologies developed through our current project, a future area of interest includes studying the impact of pricing dynamics on customer expectations and satisfaction levels, a topic of increasing relevance. This approach not only aligns with current market trends but also opens avenues for more targeted and efficient customer engagement strategies.

## Section 1

### I. Problem and Opportunity Space

[Author: MEL, RL; Editor: EAO] One of the big challenges with e-commerce is how to address customer satisfaction. Tech companies, especially those in the e-commerce or online delivery sectors, place a strong emphasis on customer satisfaction. Satisfied customers lead to increased loyalty, improved brand image, and the potential for further growth. However, when dealing and interacting with humans, a lot of psychology and uncertainty are involved. An example of an interaction is the peak-end rule. ~~The peak-end rule is~~ a psychological theory that states people's judgment of an experience is primarily based on their feelings at the peak, or intense point, and the end, rather than the average feeling across the experience [1]. The application of this theory in online deliveries would then imply that actions performed at the end of a delivery process are typically valued more highly than those performed at the beginning [1].

Interesting. Does it inform your work?

[Author: MEL; Editor: ML] One quantitative way to measure customer satisfaction is through customer ratings and reviews, which are often shared with the public. Thus, analyzing and finding ways to improve this metric of customer satisfaction is critical to many businesses. This provides another problem: the customer order and rating data collected from the vast number of operations that happen all the time can be difficult to process in a meaningful way. Hence, this is where we can use emerging technologies to find a solution to this problem. In particular, machine learning can be leveraged for processing large amounts of data and revealing insights into processes that would otherwise be hard to obtain. Currently, machine learning is utilized for various intensive processing operations, including LLM's, predictive analytics, time series analysis, suggestion generators, and evaluation models [2]. Our project's focus is data analytics and data-driven decision-making, where we create machine learning models to process

Is using ML in this way a new approach in this context? Is this application the core research question? I'm not clear yet about what the project wants to know and/or what's new here.

large e-commerce datasets and draw conclusions about how various aspects of the delivery process impact customer satisfaction.

## II. Literature Review

This helps, but again, what's the unknown?

[Author: MEL; Editor: EAO, ML, RL] To reiterate, there are three problems we are addressing with this project: how to increase customer satisfaction, how to deal with large datasets, and how to draw insights from data using machine learning. Our specific objective is to employ various machine learning methodologies on e-commerce order and delivery datasets obtained by our advisor from a Chinese logistics company to analyze how different delivery attributes influence customer satisfaction. In this section, we delve into existing research discussing similar topics and technologies to our project, with the intent of getting more familiar with the problem space.

Various literature addresses methods to increase customer satisfaction from different perspectives. For example, Authors? [3] discusses the importance of customer interactions with businesses, in particular addressing how best to structure customer service information systems. Keh and Lee [4] discuss the theory of leveraging reward timing and type to increase customer satisfaction. They conducted a study revealing that satisfied customers prefer delayed, direct rewards, while dissatisfied customers opt for immediate, direct rewards [4]. Min et al. [5] explore the timing of apologies in service recovery, suggesting that customer satisfaction is enhanced when listening occurs before an apology rather than immediately apologizing, thus strengthening future interactions. Oyama et al. [6] conducted a study on e-commerce deliveries, suggesting that sometimes fast delivery is not necessary for customer satisfaction. These existing customer satisfaction observations and theories are examples of hypotheses we might want to develop or prove in the development of our machine learning models, potentially guiding our exploration of how delivery attributes impact customer satisfaction in the e-commerce domain.

There is also literature discussing various machine learning models used for processing large datasets. Chen [2] discusses and compares the usage of various machine learning models in the predictive analysis of e-commerce product sales. There are also discussions about different models for more reliable standard error computation when dealing with a variety of variables across many datasets [7] . Su, Wang, and Sun [8] present a lightweight deep-learning model used to analyze consumer data while being computationally efficient. On the technical side, literature on popular machine learning methodologies currently in use can help us explore different models and determine which ones would be most suitable for our purposes. Is this 7 & 8?

Additionally, there is a variety of literature discussing data-driven insights that can be drawn using machine learning. Kumar et al. [9] describe their process in using machine learning and deep learning to make data-driven decisions in drug discovery. Similarly, [10] describes the development of machine learning methods for optimizing treatment decisions in biomedicine. The ideas in both research papers focus on the use of machine learning strategies and the development of methods and statistical analyses, such as support vector machines, to improve small properties of their bioactivities or perform estimations for optimal treatment regimens. These goals largely parallel our own goals for improving customer satisfaction and identifying influential patterns. Therefore, although our focus is on the e-commerce industry, the methods outlined in this existing research can provide ideas for our approach to developing tools for making data-driven decisions.

## III. Methodology

[Author: MEL, EAO; Editor: EAO] Given the extensive research conducted in the realms of customer satisfaction and machine learning, our objective is to leverage the most pertinent existing research to validate and familiarize ourselves with machine learning methods commonly employed for similar data analyses. Subsequently, we aim to build upon this foundation to conduct oura nalysis on the data and derive actionable insights into how customer satisfaction can be enhanced in the order and delivery process. At a high level, our approach begins with preparing and comprehending our dataset, consisting of order and delivery logistics data obtained by our advisor from Cainiao, one of China's largest e-commerce logistics companies, for the purpose of our analysis. We will then utilize existing literature, specifically provided by our advisor, to validate the effectiveness of certain machine learning models in drawing data-driven conclusions. In this existing literature, Bray has drawn compelling conclusions about improving customer satisfaction through operational transparency, utilizing various machine learning methodologies such as quantitative linear regression estimates on similar e-commerce data [1]. Our initial focus will be on using this specific existing literature to verify if we can derive the same insights, such as the suggestion that operational transparency is most effective when delivery actions are clustered towards the end of the delivery, aligning with the peak-end effect [1]. Successfully replicating these findings would indicate that we can either expand upon this existing research or investigate our hypotheses using a similar methodology. Consequently, our next step would involve exploring new techniques and either combining them with existing methods or applying them to different aspects of the data to draw our new insights. Replication

[Author: RL; Editor: ML] To go into more detail about the technical approach, we plan to optimize our machine learning model by employing various methodologies, starting with the

Ordinary Least Squares (OLS) method for our linear regression model. Should the model exhibit a low R-squared value, indicating unreliability, we will explore alternative, possibly non-linear models. To enhance the model's applicability, we will test it against diverse variables, such as action counts and delivery speed, aiming to identify and mitigate errors for accurate future predictions. Additionally, recognizing external factors that may impact model performance is crucial; for example, the COVID-19 pandemic has introduced unexpected delays in delivery patterns. To refine our model further, we will incorporate variables from additional data sources online, leveraging external insights to improve model accuracy and reliability.

[Author: ML; Editor: EAO] Regarding data analysis, after successfully deriving existing insights, we will determine whether the data validates our hypotheses or if our new model can provide better predictions or conclusions. In particular, we might recognize results based on relationships between variables, whether through coefficients or confidence intervals or comparisons with ground truth values for predictions. An example of such a result from the research paper is where significant relationships between delivery score, action count, and day count are shown using OLS estimates of delivery score on action count and day count, with the ? gray bands depicting the estimates' 95% confidence intervals [1]. Both coefficient estimates and confidence intervals work as perfect explanation tools for drawing conclusions.

## Section 2

### I. Data

[Author: RL, EAO; Editor: EAO, MEL] In the exploration of e-commerce logistics dynamics, the application of real-world data unveils critical insights that guide operational strategies and customer satisfaction enhancements. In this project we aim to employ the extensive dataset provided by Cainiao, a prominent figure in China's e-commerce logistics landscape, capturing the complex details of order processing and delivery from January to July 2017. The data is meticulously segmented into three integral categories: Orders, Logistics, and General datasets, each offering a distinct perspective yet collectively capturing comprehensive relationships of the logistical framework.

The Orders Dataset provides a foundational understanding of customer interactions, capturing essential aspects such as order placement, item specifications, and promised delivery speeds. The data connects directly with customer experiences and expectations, offering a lens into the demand-side dynamics of e-commerce. Concurrently, the Logistics Dataset reveals the operational side of Cainiao, narrating the parcels' journey across various logistical milestones. Here, data points like shipment routes, delivery actions, and timelines are pivotal in dissecting the logistical process and identifying efficiency levers or potential bottlenecks.

Lastly, the General Dataset broadens the analytical horizon to encompass inventory management, item classification, and merchant details, thereby embedding the delivery data within the larger context of supply chain and market dynamics. This dataset enriches the analysis by linking logistical operations with broader business strategies and market trends, providing a holistic view of the e-commerce ecosystem.

Central to our analysis are key independent variables that emerge from the datasets as focal points for our research: the granularity of action time and count highlights the operational tempo and procedural intricacies of the delivery process, while day count offers insights into the network's speed and reliability. Promise speed, a critical benchmark for customer expectations, and item price reflecting the perceived value spectrum, are evaluated to determine their contribution to achieving delivery goals. At the core of our inquiry is the logistic review score, a quantified reflection of customer satisfaction, serving as the ultimate dependent variable for assessing the efficacy of Cainiao's logistics operations.

The analysis of this dataset is not merely academic; it holds real-world benefits, to gain an understanding of the relevant industry standards and create new strategic ways for operational excellence. By aligning operational metrics with customer satisfaction indicators, the exploration aspires to highlight potential methods of service enhancement and competitive differentiation in the diverse world of e-commerce logistics. Through this analytical process, the aim is to distill actionable conclusions that can inform both Cainiao's future endeavors and broader industry practices with Cainiao's provided data, underscoring the pivotal role of data-driven insights in advancing customer-centric logistics.

## II. Experimentation

[Author: RL, EAO; Editor: EAO, MEL] In the experimentation phase, the team adopted a systematic approach, aimed at gathering insights into the complexities of customer satisfaction within e-commerce logistics. The foundational step involved a thorough validation of existing findings by replicating a research study within this domain. This replication served not just as a credibility check for the adopted methodologies but also established a baseline for our subsequent analysis.

If this is the backbone of your work, it's worth getting into a bit more detail about methods and findings.

Our approach was divided into validation and exploration phases. Initially, we focused on replicating the results from a notable research paper, which applied various machine learning models to understand customer satisfaction dynamics in e-commerce. By adopting similar models, such as linear regression, time series analysis, and neural networks, we aimed to validate these established insights, thereby affirming the robustness of our analytical framework.

Author?

Following the replication, our experimentation primarily shifted to focus on the exploratory domain. We tailored our models to dissect important attributes of order data, thereby enhancing our grasp on the varied nature of logistic operations and their impact on customer perceptions. This phase was crucial for extending beyond the existing research, allowing us to depict nuanced insights, particularly around the peak-end rule, the timing of logistic actions, and the differential impacts of holiday versus non-holiday periods on customer satisfaction.

Say this in the intro and clarify that you'll answer these questions separately below.

In the realm of data preparation, thorough data cleaning was paramount. We removed poorly documented records and records with any deficiencies in action counts and standardized date formats for uniformity. Such preliminary steps ensured the integrity and consistency of our dataset, laying a solid foundation for subsequent analysis.

Statistical and machine learning methodologies underpinned our exploration. While Ordinary Least Squares (OLS) provided initial estimations, we further leveraged Two-Stage Least Squares (2SLS) for a nuanced understanding of causal relationships within our data. Progressing from these foundational analyses, we segmented our data into subgroups to scrutinize the various impacts of pricing strategies, delivery promises, and seasonal fluctuations.

Furthermore, the team deployed an artificial neural network model. This model was intricately designed, incorporating variables that emerged as significant across our segmented analyses. By training this network to predict the customer satisfaction score, the complex interplay of various determinants was captured in an attempt to offer a holistic view of the primary factors influencing customer satisfaction in e-commerce logistics.

The experimentation phase not only enhanced our understanding of the logistical determinants of customer satisfaction but also equipped us with empirical insights that could guide strategic optimizations in the e-commerce logistics sector.

## III. Results

**1.** Application of the Peak-End Rule in E-commerce Logistics Customer Satisfaction

This is explained above

[Author: EAO; Editor: MEL] Consumers base their experience with a company largely on how they felt at the experience's peak, which can be either the most intense point of the interaction or at its end, rather than the total sum or average of every moment of the total process [1]. Understanding these nuances of the customer experience is pivotal for fostering satisfaction and loyalty. In this segment of our analysis, we delve into the application of the Peak-End Rule, a psychological principle suggesting that people's evaluation of an experience is disproportionately influenced by its most intense point (peak) and its conclusion (end). In the context of e-commerce, we hypothesize that increased actions during the end stages of the delivery process play a critical role in shaping overall customer satisfaction.

Our methodological approach involved a detailed examination of delivery action data, focusing on the percentage of interactions out of each delivery's total interactions that were recorded during the final stages of delivery. The final stage is specified as the interval starting from 80% of the overall delivery time to the end of the delivery. By comparing customer satisfaction scores associated with different percentages of the total interactions that occur in the final stages of delivery, we sought to discern patterns that could substantiate the Peak-End Rule's relevance in this setting.

Say this at the beginning

Detailed data analysis in Fig. 1 revealed that customer satisfaction scores increased by an average of 0.1 when 70% of a delivery's total actions occurred during the last 20% of the delivery timeline, compared to when only 10% of the total actions occurred during this period. This increase in satisfaction was most significant when comparing the amount of later interactions to early-stage communications, with the lowest satisfaction scores observed when significant updates occurred early on in the delivery process.

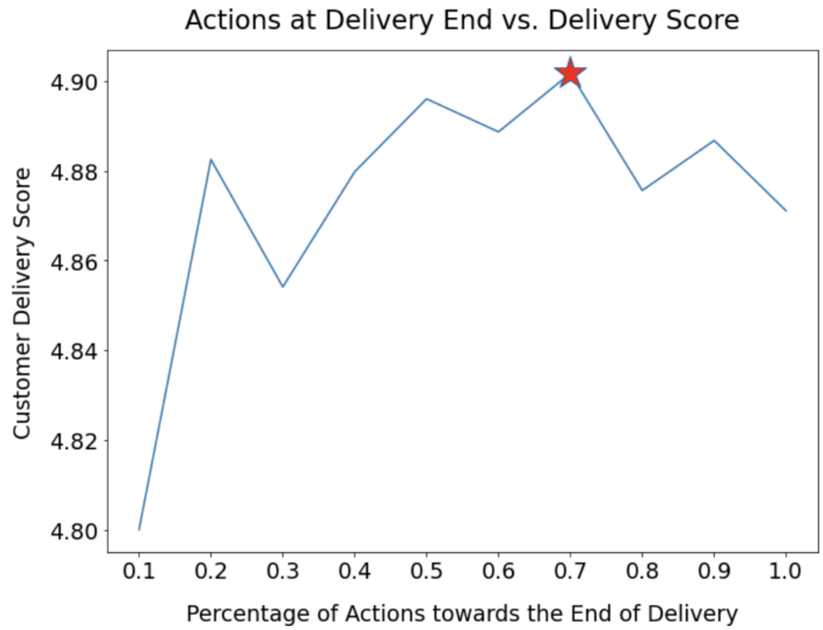


Fig. 1. Peak-End Rule Visualization for Final Stage Delivery Actions Impact on Satisfaction

Such results offer compelling evidence supporting the Peak-End Rule's application within e-commerce logistics. The intensified positive perceptions and higher satisfaction ratings associated with a burst of later-stage delivery interactions suggest that customers value and remember these concluding experiences more vividly. This tendency aligns with the psychological expectation that the end of an experience significantly frames one's overall perception, lending greater weight to these final moments.

The implications of these insights are profound for the e-commerce logistics sector. By understanding and leveraging the Peak-End Rule, companies can strategically enhance customer satisfaction by focusing on enriching the delivery experience's final phases. This might include optimizing communication strategies to ensure timely and impactful updates during the delivery's conclusion or even reevaluating operational protocols to maximize positive customer interactions at these critical junctures.

Our analysis not only reaffirms the Peak-End Rule's psychological validity but also translates it into actionable conclusions for e-commerce logistics. By prioritizing and enhancing end-stage customer interactions, businesses can significantly elevate the overall customer experience, driving satisfaction, and loyalty, potentially influencing future purchasing decisions. This strategic focus on the delivery process's concluding phase emerges as a key differentiator in the competitive landscape of e-commerce and further improves customer relationships in the e-commerce sector.

## **2.** Action Timing in E-commerce Logistics and Its Impact on Customer Satisfaction

[Author: EAO; Editor: MEL] In exploring the complex dynamics of e-commerce logistics, our study delves into the strategic significance of delivery action timing on customer satisfaction. Leveraging relevant analytical tools, we explored how the timing of specific delivery-related actions correlated with customer ratings, uncovering patterns that underscore the nuanced expectations consumers have regarding delivery notifications.

To gain these insights, a regression analysis was employed that combined linear regression with a simple time series component, offering a predictive understanding of how action timing influences customer perceptions. Our regression analysis focused on two distinct categories of delivery actions: 'early actions' such as 'got' and 'departure' (denoted in figures as: 'GOT' and 'DEPARTURE'), signaling the initiation of the delivery process, and 'late actions' like 'arrival' and 'sent scan' (denoted in figures as: 'ARRIVAL' and 'SENT_SCAN'), signaling the final stages of the delivery process. This analysis is depicted in Fig. 2, illustrating the average logistic review score for each timing decile of these actions, providing an illustration of customer preferences throughout the delivery timeline.

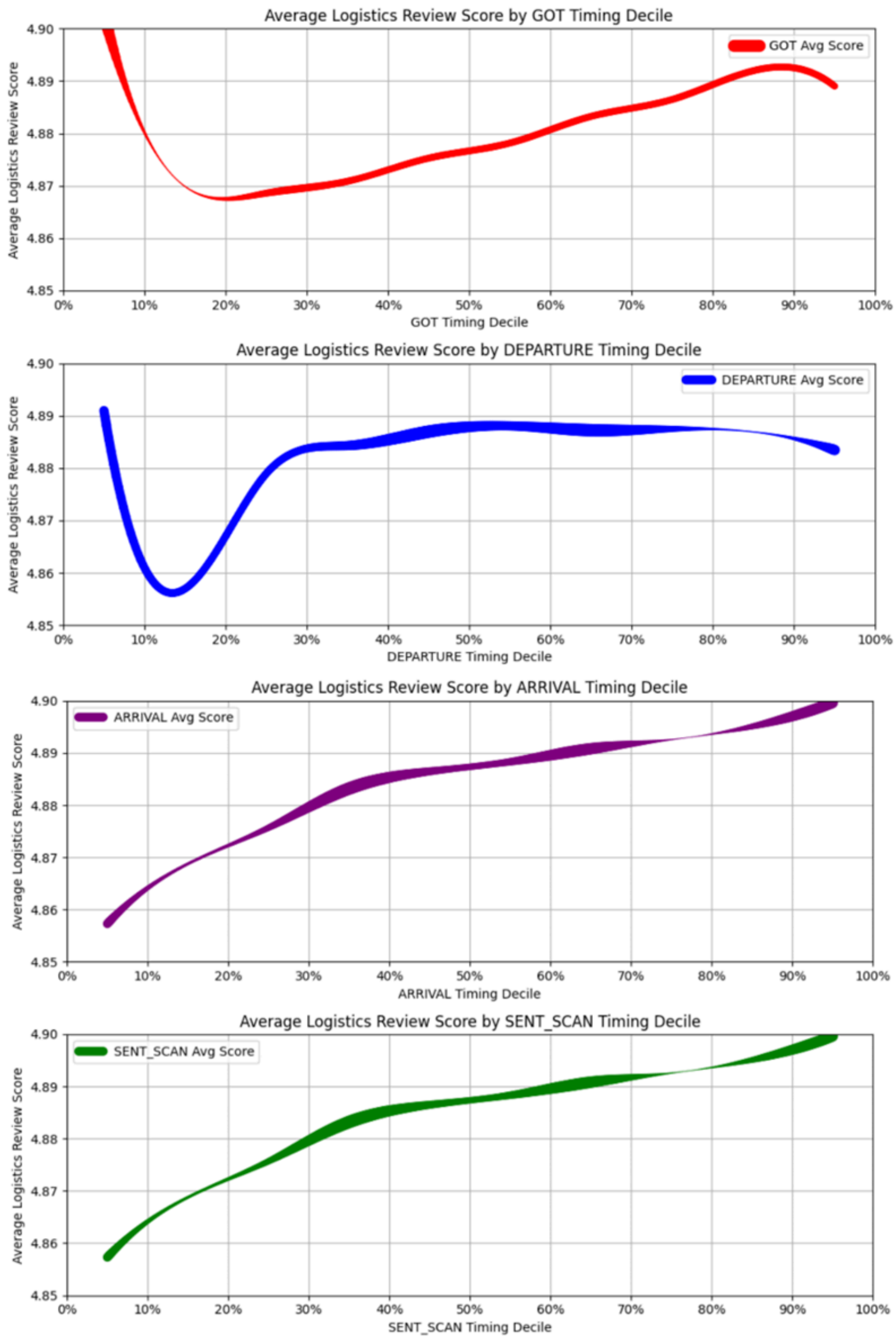


Fig. 2. Action Timing of Early and Late Actions' Impact on Satisfaction

What does a 0.05% change mean for a company?



The findings for early actions were informative. The graph revealed that customer satisfaction peaked when notifications about early actions were issued immediately after product dispatch — within the 0-10% timing decile — achieving an average score of around 4.9. However, there was a noticeable dip to approximately 4.85 in satisfaction scores when notifications were delayed to the 10-20% decile, suggesting a customer preference for immediate transparency at the delivery's outset. The score then modestly improved, suggesting that while customers value prompt initial updates, their satisfaction slightly recovers even if subsequent communications are less immediate.

Conversely, later actions demonstrated a different pattern. Customer satisfaction progressively increased with these notifications being most valued towards the delivery's conclusion, particularly in the 90-100% decile. This linear escalation aligns with our earlier findings related to the Peak-End Rule, reinforcing the idea that effective communication toward an experience's end significantly boosts customer perception.

Notably, our analysis identified potential areas for optimization. A substantial proportion of early actions were either overly concentrated at the beginning or too dispersed, suggesting an opportunity to enhance satisfaction by strategically clustering these notifications. Meanwhile, later actions, predominantly situated in the mid-delivery phase, could potentially elevate customer satisfaction if shifted closer to the delivery's end, as suggested in earlier findings.

Our findings on action timing showcase how the scheduling of delivery notifications influences customer satisfaction. This approach prioritizes strategic alignment by communicating early actions promptly and highlighting later actions upon delivery completion, thereby optimizing customer satisfaction throughout the process. Ultimately, these approaches to action timing highlight a fundamental shift towards more anticipative and responsive e-commerce logistics strategies, ensuring customer satisfaction guides every aspect of logistical decisions.

**3.** Seasonal Holiday Analysis in E-commerce Logistics: Navigating Customer Satisfaction Amid Increased Demand

[Author: EAO; Editor: MEL] The Seasonal Holidays analysis within our study explores how the surge in order volumes during shopping holidays influences delivery timelines and, subsequently, customer satisfaction. Given the inherent pressures of heightened demand, our analysis aimed to discern how well an e-commerce logistics system, exemplified by Cainiao during its peak season around June 18th, manages customer expectations through strategic delivery scheduling and communication.

Our dataset comprised approximately 4 million orders classified as non-holiday and 700,000 orders during the defined holiday period (June 8th to 28th), enabling a robust comparison across various delivery timings: 'really late', 'late', 'on time', 'early', and 'really early' (denoted in figures as: 'Really_Late', 'Late', 'On_Time', 'Early', and 'Really_Early'). This classification was based on the alignment between promised and actual delivery times, offering insights into how timely delivery—or its absence—impacts customer perceptions.

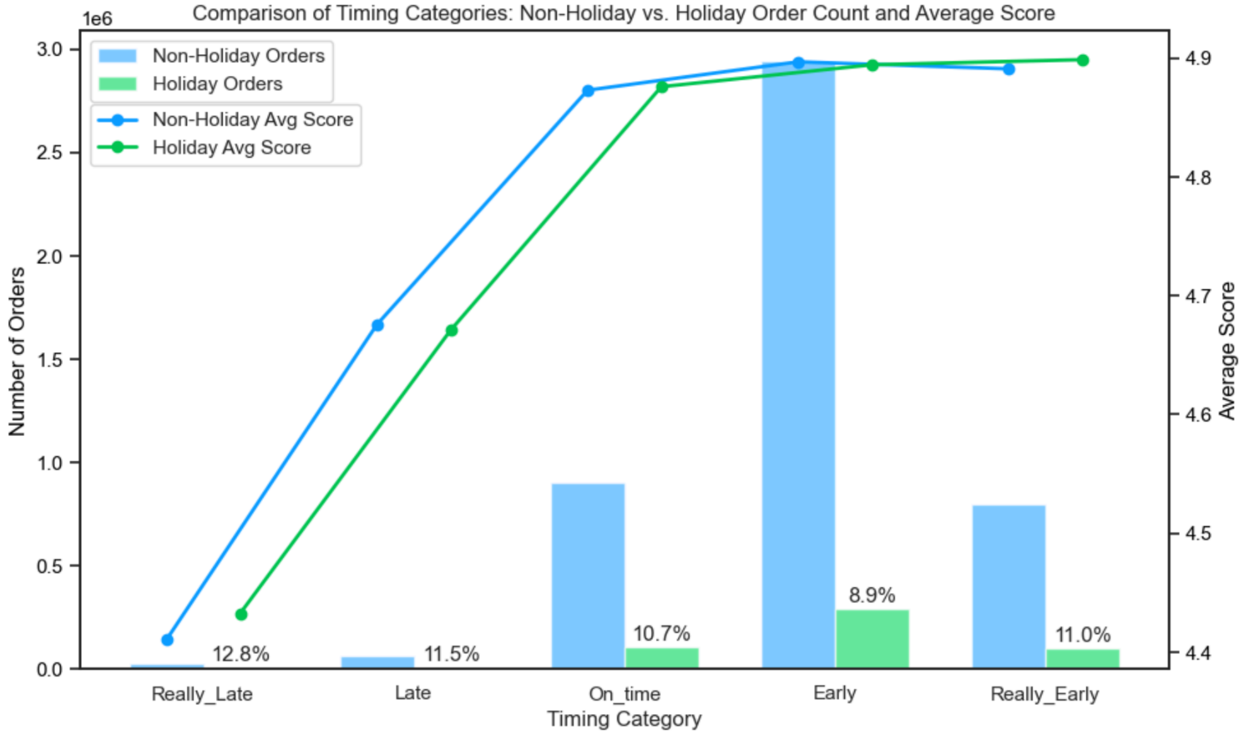


Fig. 3. Non-Holiday vs. Holiday Order and Timing Comparisons with Satisfaction

When comparing satisfaction scores across these timing categories during both holiday and non-holiday periods in Fig. 3, a key observation was the distribution of orders predominantly skewing towards 'early' and 'on time' deliveries, with significantly fewer instances in the 'late' and 'really late' categories. Crucially, the data underscored a direct relationship between delayed delivery and diminished satisfaction: scores tapered from an average of 4.9 for 'on time' deliveries down to 4.4 for 'really late' cases.

Surprisingly, the comparative analysis revealed no discernible difference in satisfaction scores between holiday and non-holiday periods across all timing categories, suggesting an effective adaptation by the logistics system during peak times. This was further highlighted by examining the proportion of holiday orders relative to non-holiday figures across categories, revealing strategic efforts to prioritize early deliveries despite the surge, thereby mitigating potential downticks in satisfaction.

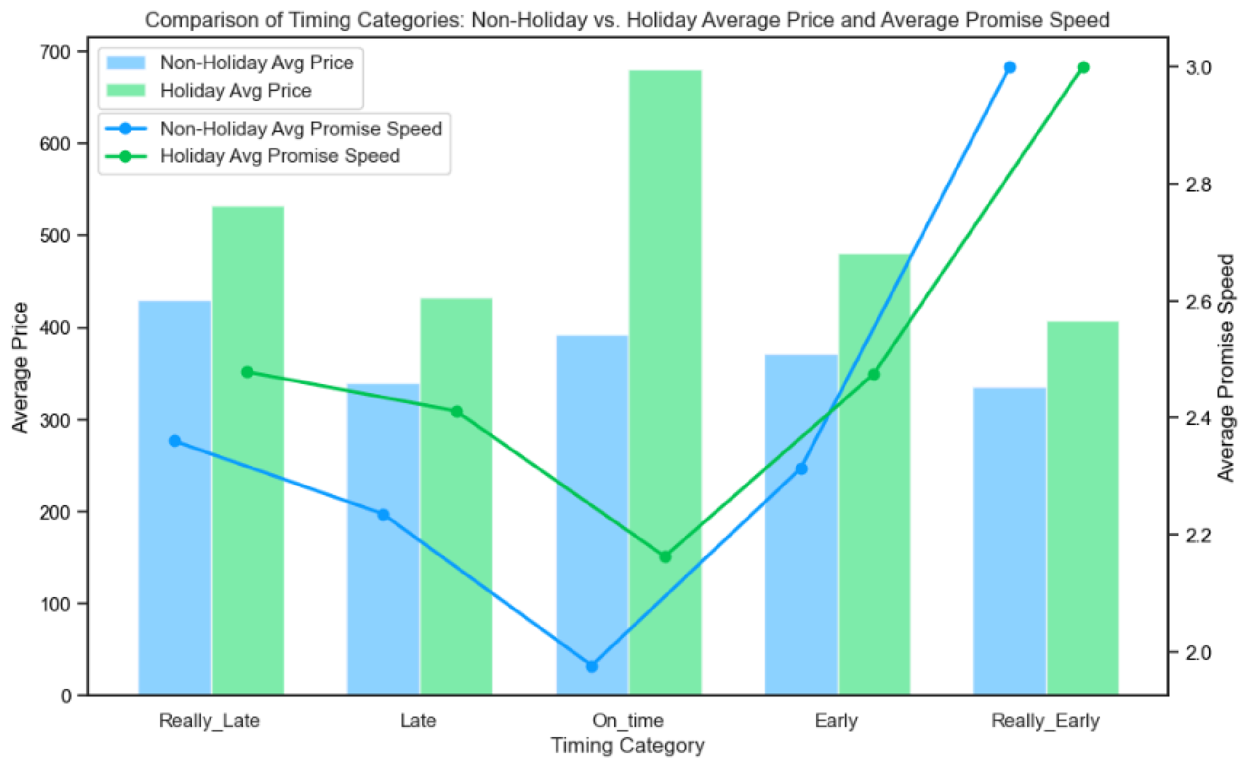


Fig. 4. Non-Holiday vs. Holiday Promise Speed and Price Comparisons with Satisfaction

The analysis of order attributes during the holiday season further compares the average order price and delivery promise speed across the delivery timing categories in Fig. 4. Notably, the 'on time' category during the holiday season is distinguished by a higher average order price compared to non-holiday periods, suggesting a strategic emphasis on ensuring timely delivery for higher-valued items. This approach likely aims to safeguard customer satisfaction by prioritizing the punctuality of deliveries that customers may perceive as more significant or urgent due to their higher value. The data indicates that this strategy could be important to maintain high satisfaction scores, as timely deliveries are crucial for customer perception, especially when it concerns premium orders.

From examining 'really early' and 'really late' delivery categories, a pattern starts to develop. The extended promise speeds for 'really early' deliveries appear to set conservative expectations, allowing the firm to consistently meet anticipated delivery times, thereby boosting satisfaction. Conversely, the high average prices for 'really late' deliveries, maintained across both holiday and non-holiday contexts, might reflect a calculated trade-off between maximizing revenue and managing customer expectations. This pricing strategy, particularly during high-demand periods, showcases the company's balancing of operational efficiency and customer satisfaction, offering a method that could inform best practices in logistics management.

In summary, this analysis offers a window into the logistical dexterity of e-commerce operations during critical shopping periods. Despite the inevitable uptick in order volumes, strategic delivery timing and enhanced promise speeds appear pivotal in maintaining, if not enhancing, customer satisfaction for Cainiao. These insights demonstrate not only the company’s operational experience but also serve as a valuable blueprint for other logistic entities aiming to sustain customer satisfaction levels during seasons of amplified demand.

## 4. Neural Network Model for Customer Satisfaction Prediction

[Author: ML; Editor: EAO, MEL] In the realm of predictive modeling, the performance disparity between linear regression (LR) and neural networks (NN) is noticeably pronounced. Utilizing a linear model, which included promise speed, price, actual speed days, and action count as independent variables, to predict scores reveals a substantial discrepancy between actual and predicted values. This method's lower predictive accuracy is further evidenced by the plotted data points in Fig. 5, which significantly deviate from the identity line y = x. This supports the fact that the dataset itself cannot fit this linear model quite well.

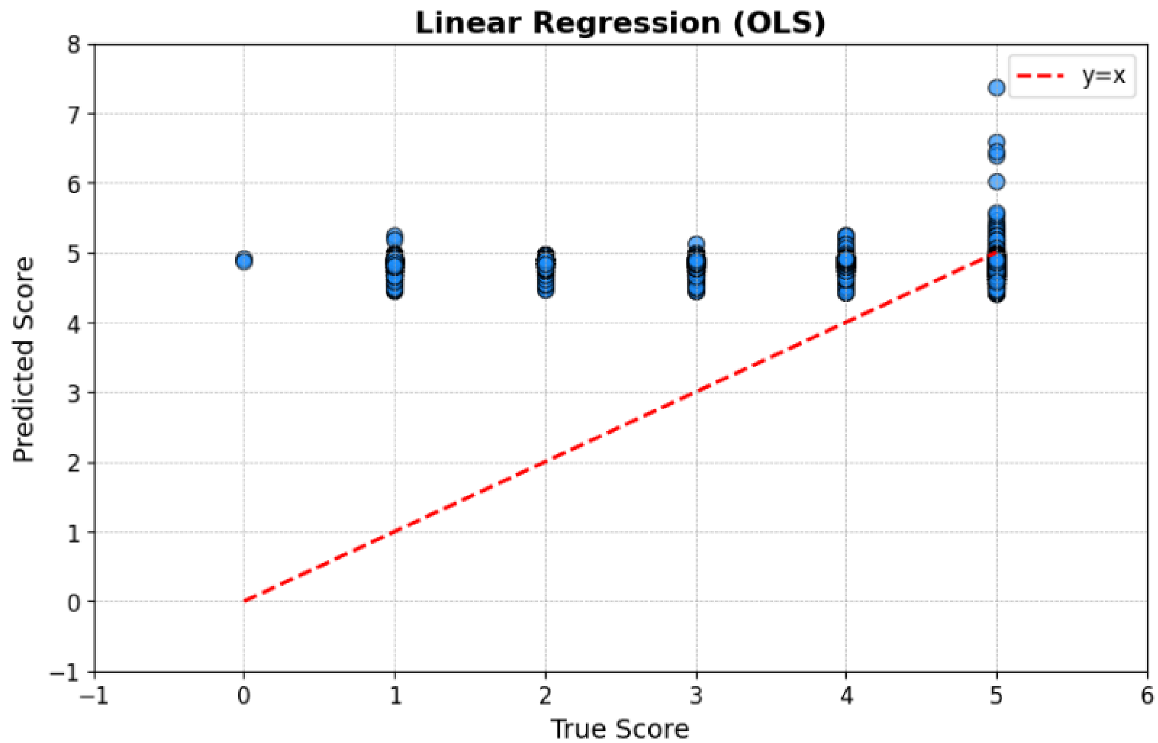


Fig. 5. Linear Regression Model Predictive Accuracy

Shifting our focus to the NN model, we observe a contrasting result. The NN architecture, featuring two hidden layers with 128 and 256 neurons respectively, showcases exaggerated prediction capability. Utilizing the same dataset as the LR model, NN further applies 3-fold cross-validation and test validation to avoid overfitting, leading to an impressively low loss between true and predicted scores, consistently falling below 0.265.

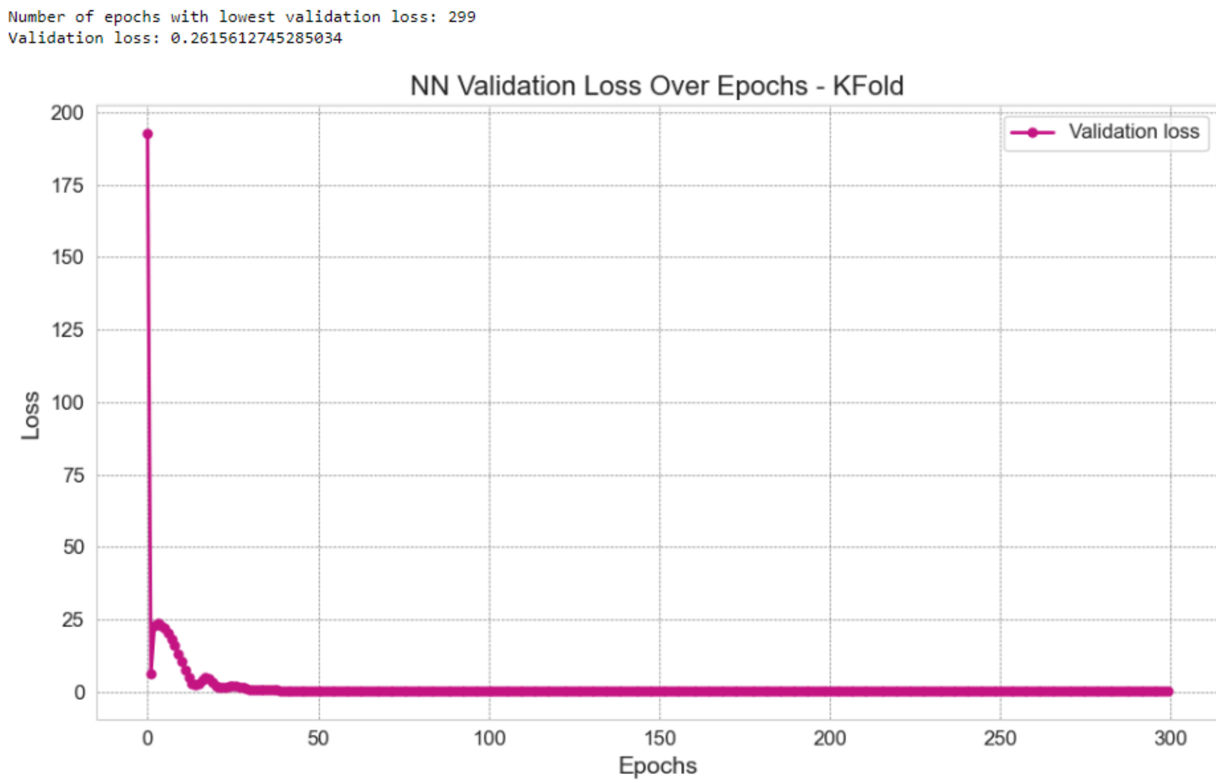


Fig. 6. Neural Network Predictive Model Predictive Validation Loss

The low losses achieved through the NN model could make it a valuable tool for merchants to predict logistics review scores, potentially providing a strategic advantage in enhancing customer satisfaction. The feature ablation analysis in Fig. 7, which investigates the effect of component removal on the performance of machine learning models, reveals the influential parameters within the NN model. Upon analyzing these parameters in the NN model, we found 'price' and 'action count' to be pivotal features. Their omission leads to a substantial increase in prediction loss of 2.44 and 2.46 respectively, highlighting their contribution to this model's predictive accuracy. On the other hand, parameters like 'promise speed' and 'actual speed days' seem to have negligible impacts on the predictive accuracy according to our model. However, it is important to note that these results are derived from a simplified NN model. They may not align with previous findings and do not necessarily reflect universal truths or conclusive evidence, thereby necessitating a critical examination.

Is this graph saying anything beyond 2.44 & 2.46? Is it needed?

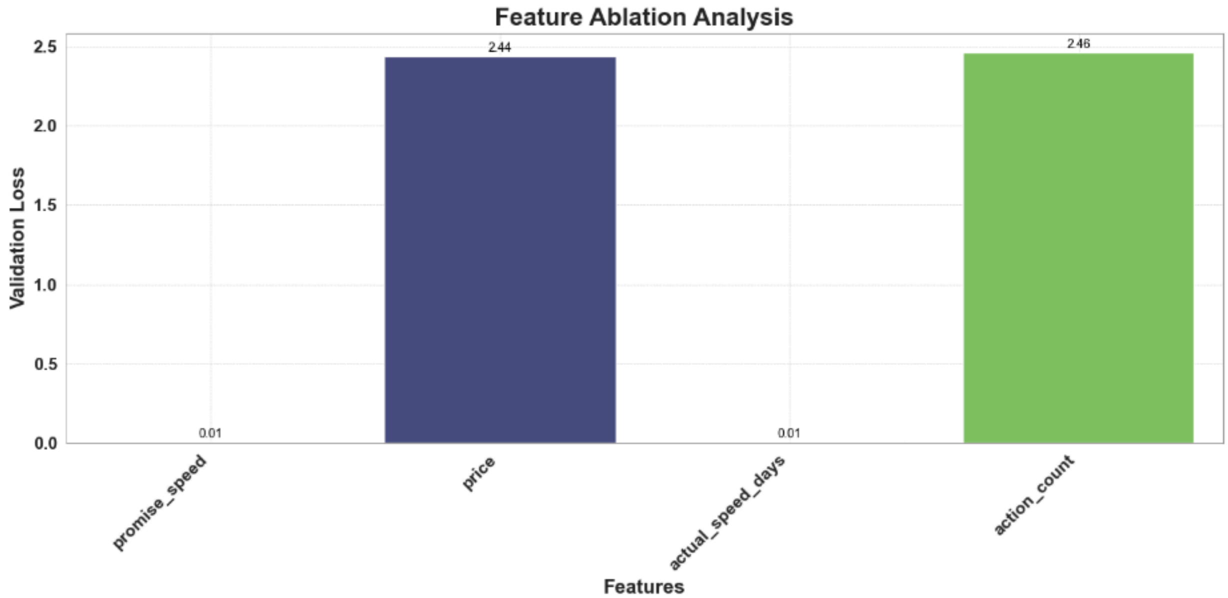


Fig. 7. Neural Network Model Feature Ablation Results

## IV. Conclusion

[Author: EAO; Editor: MEL] In this concluding section of our study, we summarize our key findings and their implications for the e-commerce logistics sector, focusing on data-driven decision-making and the use of advanced machine learning models. Our research aimed to analyze the effects of various logistic parameters, such as delivery speed and action timing, on customer satisfaction in the e-commerce environment.

With the replication of a relevant study within the e-commerce industry, we were able to reinforce the reliability and credibility of our experimental framework and gain a solid comparative baseline for our analysis. This initial phase was crucial for ensuring that our investigation stood on firm empirical ground. Subsequently, we expanded the scope of our

Is this the key? Replicate, then add regression?



inquiry by employing regression analysis to explore and quantify the influence of a broader array of attributes on customer satisfaction within the e-commerce logistics sector. This phase allowed us to delve into less examined variables and their potential impacts, thus broadening our understanding and allowing for unique insights.

Our study notably affirmed the peak-end rule's relevance in logistics, illustrating how customers' final interactions with the delivery process profoundly shape their overall satisfaction. This principle, deeply rooted in psychological insights, emphasizes the lasting impact of the delivery's concluding moments on customer perception and memory. Concurrently, our findings brought to light the significant drawbacks of delivery delays, showcasing how such incidents directly diminish customer satisfaction and could adversely affect the likelihood of repeat business. The implications of these insights are far-reaching, suggesting that timely and effective delivery closures are not just operational goals but critical points that can enhance customer loyalty and drive competitive advantage in the e-commerce landscape. By addressing these key moments and mitigating any significant delays, businesses can develop stronger relationships with their customers, underpinning long-term success and customer engagement.

The practical implications of our research extend beyond immediate logistical strategies, providing directions to navigate the complexities of e-commerce customer satisfaction. By identifying actionable levers for enhancing the customer experience, our study underscores the necessity of agility and foresight in logistics management. Such adaptability and continuous improvement are crucial for businesses aiming to maintain relevance and excel in customer engagement amidst the relentless pace of change in the sector.

In terms of further work, one avenue would be to examine order pricing dynamics more thoroughly alongside logistic performance and customer satisfaction. The current results indicate

Price of product? Shipping? Both?



that despite the significant price elevation during the holiday season, customer satisfaction scores remained unaffected. Utilizing advanced analytical frameworks such as Support Vector Machines or Gradient Boosting could enable a more granular analysis of this dynamic, revealing more intricate relationships. Such an analysis could potentially unveil strategies to optimize pricing without impairing customer satisfaction. This, in turn, could offer more holistic strategic deployment methods within the e-commerce logistics sector. Another avenue would be to do a deep dive into the impact of same-day delivery on customer satisfaction, a key market trend. Insights gained into same-day deliveries and their impact on review scores could have significant implications for companies in terms of striking an optimal balance between operational efficiency and customer satisfaction.

In conclusion, this study enhances our collective understanding of leveraging data-driven insights to improve e-commerce logistics operations. While it identifies several pivotal factors impacting customer satisfaction, it also underscores the importance of continuous research and evolution in the methodologies and strategies employed. As the e-commerce landscape grows, analytical and operational approaches must adapt accordingly. By encouraging ongoing investigation and the practical application of research findings, we hope to foster further collaborative advancement in the field of e-commerce logistics and customer satisfaction.

**Legend**

EAO - Egill Oktosson

ML - Minke Lu

MEL - Michelle Lu

RL - Ruoyu Liang

**References**

[1] R. L. Bray, “Operational Transparency: Showing When Work Gets Done,” *Manufacturing & Service Operations Management*, vol. 25, no. 3, pp. 812–826, Oct. 2020. doi:10.1287/msom.2020.0899

[2] N. Chen, “Research on E-commerce database marketing based on machine learning algorithm,” *Computational Intelligence and Neuroscience*, vol. 2022, pp. 1–13, Jun. 2022. doi:10.1155/2022/7973446

[3] E. Grigoroudis and Y. Siskos, “Customer satisfaction and information systems,” *International Series in Operations Research & Management Science*, vol. 139, pp. 263–285, Oct. 2009. doi:10.1007/978-1-4419-1640-2_9

[4] H. T. Keh and Y. H. Lee, “Do reward programs build loyalty for services?the moderating effect of satisfaction on type and timing of rewards,” *Journal of Retailing*, vol. 82, no. 2, pp. 127–136, 2006. doi:10.1016/j.jretai.2006.02.004

[5] K. S. Min *et al.*, “Timing of apology after service failure: The moderating role of future interaction expectation on customer satisfaction,” *Marketing Letters*, vol. 31, no. 2–3, pp. 217–230, Jun. 2020. doi:10.1007/s11002-020-09522-y

[6] Y. Oyama, D. Fukuda, N. Imura, and K. Nishinari, “Do people really want fast and precisely scheduled delivery? E-commerce customers’ valuations of Home Delivery Timing,” *Journal of Retailing and Consumer Services*, vol. 78, pp. 1–16, May 2024. doi:10.1016/j.jretconser.2024.103711

[7] D. Pacini and F. Windmeijer, “Robust inference for the two-sample 2SLS estimator,” *Economics Letters*, vol. 146, pp. 50–54, Sep. 2016. doi:10.1016/j.econlet.2016.06.033

[8] Y. Su, C. Wang, and X. Sun, “Lightweight Deep Learning Model for marketing strategy optimization and characteristic analysis,” *Computational Intelligence and Neuroscience*, vol. 2022, pp. 1–9, Aug. 2022. doi:10.1155/2022/2429748

[9] S. A. Kumar *et al.*, “Machine learning and deep learning in data-driven decision making of drug discovery and challenges in high-quality data acquisition in the pharmaceutical industry,” *Future Medicinal Chemistry*, vol. 14, no. 4, pp. 245–270, Dec. 2021. doi:10.4155/fmc-2021-0243

[10] D. Luckett, “Machine Learning for Data-Driven Biomedical Decision Making,” dissertation, 2018

**Academic Integrity**

We affirm that we are the sole authors of this report and we give due credit (i.e., use correct citations) to all used sources. (ENGIN 295 UC Berkeley 2024)

| | |
|---|---|
| *Egill Oktosson* | April 11, 2024 |
| Egill Oktosson | |
| *Michelle Lu* | April 11, 2024 |
| Michelle Lu | |
| *Minke Lu* | April 11, 2024 |
| Minke Lu | |
| *Ruoyu Liang* | April 11, 2024 |
| Ruoyu Liang | |

**Turnitin Reflection**

The Turnitin score is currently 8%. We discuss the matches below:

The cover page contains a match, but it is the standard template we are all using for the paper.

The table of contents contains matches, but they are for common section headers used in papers.

Page 2 contains matches, but it describes the peak-end rule and has an in-text citation.

Page 4 contains matches, but they are for phrases such as “machine learning models” and “machine learning and deep learning”, which are common technological terms.

Page 6 contains matches. One is for the explanation of a result in a research paper that we are using for the project, which has an in-text citation. The other is a match for phrases such as “e-commerce logistics”, which is a common phrase for this problem space.

Page 10 contains a match, but it describes the peak-end rule again and has an in-text citation.

Pages 11 and 23 contain matches, again for the common phrase "e-commerce logistics".

Page 15 contains matches for the delivery timing categories we determined and used in our data analysis, not from any other outside sources.

Pages 24-25 contain matches for the references and the academic integrity pledge. The reference citations are present, and the academic pledge is part of a standard template.

+

Findings and overall structure are clear

Good use of sources, but . . .

Good discussion of how the findings might be applicable to businesses.

−

The opening sections identify broadly what the project wants to find out, but it's not clear what unknowns it wants to answer. If it's a replication study (5), say so.

→ Talk in more detail about the study you're replicating – it's the foundation of your work.

Say at the beginning that you're interested in the three key aspects discussed on p. 9, plus regression if that's a key methodological piece (22).

Overall, what's here is good; I'm just not clear on what the project actually wants to know.

A− / B+