

**REQUEST ACCEPTANCE PREDICTION AND
COURIERS' CONTINUED PARTICIPATION
MODELS IN CROWDSOURCED
LAST-MILE LOGISTICS
IN SAUDI ARABIA**

BY

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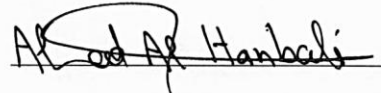
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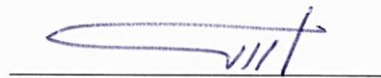
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I dedicate this thesis to my parents, my wife, and my sons, whose constant support and love have been my greatest strengths. I am profoundly grateful to my entire family for their encouragement and sacrifices that have supported me through this journey.

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TABLE OF CONTENTS

Contents

ACKNOWLEDGMENTS	V
TABLE OF CONTENTS.....	VI
LIST OF TABLES.....	VI
LIST OF FIGURES.....	X
LIST OF ABBREVIATIONS.....	XI
ABSTRACT.....	XIII
ملخص الرسالة.....	XV
CHAPTER 1 INTRODUCTION.....	1
1.1 Crowdsourced in Last Mile Delivery	1
1.2 Factors influencing the continued participation of individuals as crowdsourcing couriers. ...	6
1.3 Prediction Model of courier’s acceptance probability of delivery tasks.....	10
1.4 Problem Statement.....	12
1.5 Research Motivation.....	14
1.5.1 Managerial Motivation	14
1.5.2 Academic Motivation	15
1.6 Research Objective	17
1.7 Contributions of the Research.....	17
1.8 Thesis Outline	19
CHAPTER 2 LITERATURE REVIEW	20

2.1	Crowdsourced last mile delivery	20
2.2	Review of research on continued couriers' participation behavior in crowdsourcing	23
2.2.1	Social Exchange Theory Model (SETM)	27
2.2.2	Extended Unified Theory of Acceptance and Use of Technology (UTAUT2)	28
2.3	Probability of couriers' acceptance of delivery tasks as crowdsourced delivery courier.	31
CHAPTER 3 DEVELOPMENT MODEL AND METHODOLOGY		40
3.1	A Continued Couriers' Behavioral Intention Model	40
3.1.1	Development of a Continued Couriers' Behavioral Intention Model	40
3.1.2	Hypotheses:	43
3.1.3	Methodology of a Continued Couriers' Behavioral Intention Model.....	49
	a. Survey Design	49
	b. Data collection and sampling	50
3.2	Courier Acceptance Probability of Requests Model	52
3.2.1	Predictive Modeling Techniques.....	52
3.2.2	Methodology of Acceptance Probability Model	68
CHAPTER 4 DATA ANALYSIS AND RESULTS OF CONTINUED COURIERS' BEHAVIORAL INTENTION MODEL		77
4.1	Data Analysis and Results of Continued Couriers' Behavioral Intention Model	77
4.1.1	Descriptive Results	77
4.1.2	Measurement Model Assessment	79
4.1.3	Structural Model Assessment.....	84
4.1.4	Common Method Bias (CMB)	87
4.1.5	Multi-collinearity and autocorrelation test	88
4.1.6	Endogeneity test	89
4.1.7	Multigroup Analysis	90

CHAPTER 5 DATA ANALYSIS AND RESULTS OF REQUEST ACCEPTANCE PROBABILITY MODEL	94
5.1 Data Analysis and Results of Request Acceptance Probability Model	94
5.2 Sensitivity Analysis and Results of Request Acceptance Probability Model	104
CHAPTER 6 DISCUSSION AND IMPLICATIONS OF THE RESEARCH	109
6.1 Discussion of Continued Couriers' Behavioral Intention Model	109
6.2 Implications of the Research	114
6.2.1 Theoretical Implications	115
6.2.2 Managerial Implications	116
6.3 Discussion of Request Acceptance Probability Model	117
CHAPTER 7 CONCLUSION, LIMITATIONS, AND FUTURE WORK	121
7.1 Conclusion	121
7.2 Limitations and Future work	123
REFERENCES	125
VITAE	151
PUBLICATIONS	151
APPENDICES	154

LIST OF TABLES

Table 1	Factors influencing couriers' behavior in crowdsourced delivery from prior studies.....	30
Table 2	Stated Preference (SP) influencing the acceptance probability of delivery attributes in crowdsourcing last mile Delivery.....	39
Table 3	Items Used for Couriers' Behavior in Both Online and Paper Surveys.....	51
Table 4	Task Acceptance Scenarios	68
Table 5	Example of Courier Response Data: gender, type of job, and Stated Delivery Preferences (compensation, distance, time)	69
Table 6	Detailed scenario-based analysis of courier task acceptance.....	71
Table 7	Description of Proposed Models Architecture for Acceptance Probability ..	76
Table 8	Demographic Results.....	78
Table 9	Internal reliability and convergent validity.....	82
Table 10	Results of Discriminant Validity – Fornell-Larcker criterion of Measures and Correlation Matrix and HTMT analysis.....	83
Table 11	Model fit indices	84
Table 12	Structural equation modelling outcomes	86
Table 13	Control variables for SEM analysis	86
Table 14	Path coefficients before and after CMB adjustment.....	88
Table 15	Multi-collinearity test.	89
Table 16	Endogeneity Test Using 2SLS.....	89
Table 17	Multigroup path analysis	93
Table 18	Software Specifications for Models Implementation	95
Table 19	Estimation Result for control variables	96
Table 20	ML models and prediction results	103
Table 21	ML models and sensitivity analysis results	107
Table 22	Survey Design.....	156

LIST OF FIGURES

Figure 1	Proposed couriers' continued participation behavior model (SETM-UTAUT2).....	41
Figure 2	Logistic model	53
Figure 3	Random Forest model.....	55
Figure 4	Artificial Neural Network model.....	56
Figure 5	Decision Tree model.....	57
Figure 6	Long Short-Term Memory Model.....	59
Figure 7	Support Vector Machine model.....	61
Figure 8	Extreme Gradient Boosting model	63
Figure 9	Gated Recurrent Unit model.....	65
Figure 10	Soft Voting model	67
Figure 11	Proposed Acceptance Probability Model	75
Figure 12	Demographic results	79
Figure 13	Male demographic results.....	80
Figure 14	Female demographic results	80
Figure 15	3D scatter plot for acceptance or reject tasks	97
Figure 16	Feature impact on acceptance.....	98
Figure 17	Comparison of model accuracies.....	99
Figure 18	Comparison of model precision scores.....	100
Figure 19	Comparison of model recall scores	101
Figure 20	Comparison of model F1-score	102
Figure 21	Comparing models' metrics	103
Figure 22	Logistic Regression curves for the probability of acceptance vs compensation at distance(25km) and time(20,40,60 min).....	104
Figure 23	Logistic Regression curves for the probability of acceptance vs compensation at distance(15km) and time(20,40,60 min).....	104
Figure 24	SHAP value impact features on model output	106
Figure 25	3D scatter plot of compensation, distance, time and output.....	106
Figure 26	Impact input features (compensation and distance) on output	106
Figure 27	Impact input features (compensation and time) on output	106
Figure 28	Performance comparison of sensitivity analysis models' metrics	108

LIST OF ABBREVIATIONS

(β)	:	Path(Beta) coefficient
2SLS	:	Two-Stage Least Squares
3-D	:	Three-Dimensional
AMOS	:	Analysis of Moment Structures
ANN	:	Artificial Neural Networks
APLs	:	Automated Parcel Lockers
ASV	:	Average Shared Variance
AVE	:	Average Variance Extracted
BI	:	Behavioral Intention
CAGR	:	Compound Annual Growth Rate
CAPCAB	:	Compensation-Driven Acceptance Behavior
CFA	:	Confirmatory Factor Analysis
CFI	:	Comparative Fit Index
CLF	:	Common Latent Factor (CLF)
CMB	:	Common method bias
CMIN	:	Chi-square
CNN	:	Convolutional Neural Network
CR	:	Composite Reliability
DF	:	degree of freedom
DT	:	Decision Tree
EB	:	Economic Benefit
E-commerce	:	Electronic commerce
EE	:	Effort Expectancy
EI	:	Esteem Influence
EU	:	ease of use
F1-score	:	F-measure at beta equal to 1
GRU	:	Gated Recurrent Unit
H	:	Hypothesis
HM	:	Hedonic Motivation
HTMT	:	Heterotrait-Monotrait Correlation Coefficients
IBM	:	International Business Machines
km	:	Kilometer(s)
LR	:	Logistic Regression
LSTM	:	Long Short-Term Memory
min	:	Minute(s)
ML	:	Machine Learning
MLE	:	Maximum Likelihood Estimation
MSV	:	Maximum Shared Variance
None	:	No Preference
OCs	:	Occasional Couriers
OS	:	Operation System

P	:	P value
PC	:	Perceived Concerns
PE	:	performance expectancy
PPM	:	Push-Pull-Mooring
PU	:	perceived usefulness
R²	:	Coefficient of determination
RAM	:	Random Access Memory
RF	:	Random Forest
RMSEA	:	Root Mean Square Error of Approximation
RNN	:	Recurrent Neural Network
RRM	:	Random Regret Minimization
RUM	:	Random Utility Maximization
SAR	:	Saudi Riyal
SD	:	Standard Deviation
SEM	:	Structural Equation Modeling
SETM	:	Social Exchange Theory Model
SHAP	:	SHapley Additive exPlanations
SMOTENC	:	Synthetic Minority Over-sampling Technique for Nominal and Continuous
SP	:	Stated Preference
SPSS	:	Statistical Package for the Social Sciences
SRMR	:	Standardized Root Mean Squared Residual
Stata/SE	:	Statistics And Data/ Standard Edition
SVM	:	Support Vector Machine
TLI	:	Tucker-Lewis's Coefficient.
US	:	United States
UTAUT2	:	Unified Theory of Acceptance and Use of Technology
VIF	:	Variance Inflation Factor
WA	:	Work Autonomy
WICP	:	Willingness to Intend and Continue Participation
XGBoost	:	Extreme Gradient Boosting

ABSTRACT

Full Name : Mohammed Abdulaziz Abdulrasol Alromema
Thesis Title : Request Acceptance Prediction and Couriers' Continued Participation Models in Crowdsourced Last-Mile Logistics in Saudi Arabia
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Crowdsourcing logistics addresses urban last-mile delivery challenges, relying on sustained couriers' participation for success. This study seeks to understand and predict factors influencing (i) individuals to continue participating as crowdsourced couriers and (ii) courier acceptance of a new delivery request in crowdsourced last-mile delivery in Saudia Arabia. Firstly, we propose an integrated model (SETM-UTAUT2) that combines the Social Exchange Theory Model (SETM) and extended the Unified Theory of Acceptance and Use of Technology (UTAUT2). This integrated model aims to explore this topic and provide framework for understanding demographic characteristics and the behavioral variables that influence couriers' decisions to continue participating in crowdsourcing last-mile delivery. We utilized a mixed-mode survey approach, incorporating paper and online questionnaires. A survey of 345 participants used structural equation modeling with IBM SPSS Amos 26.0 to analyze data. Findings indicate that Effort Expectancy (EE), Hedonic Motivation (HM), and Work Autonomy (WA) influence couriers' willingness to continue in crowdsourced delivery. However, Esteem Influence (EI), Economic Benefit (EB), and Perceived Concerns (PC) have no significant impact. The intention to stay on the job is influenced by the motivational differences between occasional and committed couriers. Although Economic Benefit (EB) does not

significantly affect intentions to stay in crowd logistics overall, it positively influences male and committed couriers. Secondly, through an empirical study, we identify key control factors (gender and type of job) alongside quantitative factors such as compensation, driving distance, and time on the courier acceptance of a new delivery request. Using feature selection through a Binary Logit Model and comparing ten predictive Machine Learning (ML) models, including ensemble learning models (XGBoost, RF, and Soft Voting), deep learning models (ANN, GRU, LSTM, and AlexNet), and classic machine learning models (DT, SVM, and LR), we evaluate their performance across multiple metrics (Accuracy, Precision, Recall, and F1-score). Ensemble and deep learning models performed exceptionally well, with XGBoost and ANN both achieving the highest accuracy (91.06%), precision (89.97%), recall (96.70% for XGBoost, 93.09% for ANN), and F1-score (91.43% for XGBoost, 91.46% for ANN). Further sensitivity analysis using extended data highlighted that both RF and XGBoost demonstrated exceptional predictive capabilities. RF and XGBoost achieved an accuracy of 95.60% and 95.49%, precision of 95.79% and 95.74%, recall of 95.45% and 96.35%, and F1-score of 95.63% and 95.50%, respectively. These models optimize task acceptance predictions by considering time-sensitive logistic requirements, thereby enhancing the efficiency of last-mile delivery operations. The research also underscores the critical role of feature selection and model tuning in achieving robust prediction performance, ultimately contributing to more effective crowdsourcing platforms and improved courier participation.

ملخص الرسالة

الاسم الكامل: محمد عبدالعزيز عبدالرسول الرميحه

عنوان الرسالة: نماذج التنبؤ بقبول الطلب والمشاركة المستمرة للسائقين في الخدمات اللوجستية للتوصيل الجماعي (خدمات التوصيل للطلبات) في المملكة العربية السعودية

التخصص: الهندسة الصناعية والنظم

تاريخ الدرجة العلمية: ديسمبر 2024 م

تعالج الخدمات اللوجستية للتوصيل الجماعي تحديات تسليم الطلبات في المناطق الحضرية، معتمدة على مشاركة السائقين المستمرة لقبول الطلبات لتحقيق النجاح. تسعى هذه الدراسة إلى فهم وتوقع العوامل التي تؤثر على قبول السائق لطلب توصيل جديد في تسليم الطلبات كمرحلة أخيرة بالاعتماد على المساهمة الجماعية. حاليًا يوجد دراسات محدودة حول نماذج التنبؤ للأفراد لاستمرار المشاركة كسائقين في قبول مهام التوصيل. لهذا تسهم دراستنا بشكل كبير في فهم العوامل التي تؤثر على سلوك السائقين لمواصلة المشاركة في توصيل الطلبات بالاعتماد على المساهمة الجماعية وتوقع احتمال قبول الطلبات في المملكة العربية السعودية. أولاً، نقترح نموذجًا متكاملًا (SETM-UTAUT2) يجمع بين نموذج التبادل الاجتماعي (SETM) والنظرية الموحدة والموسعة لقبول واستخدام التكنولوجيا (UTAUT2). يهدف هذا النموذج المتكامل إلى استكشاف هذا الموضوع وتوفير إطار لفهم الخصائص الديموغرافية والمتغيرات السلوكية التي تؤثر على قرارات السائقين لمواصلة المشاركة في توصيل الطلبات كمرحلة أخيرة بالاعتماد على المساهمة الجماعية. يتم استخدام أدوات التعلم الآلي وبرنامج SPSS لتحليل البيانات لضمان النتائج القوية. لقد استخدمنا نهج استطلاع مختلط، يجمع بين الاستبيانات الورقية وعبر الإنترنت. حيث تم جمع عينة الاستبانة والتي تضم 345 مشاركًا وتم تحليل نتائجها باستخدام نمذجة المعادلات الهيكلية (IBM SPSS Amos 26.0). تشير النتائج إلى أن توقعات الجهد (EE)، الدافع الحسي (HM)، والحرية في العمل (WA) تؤثر على استعداد السائقين للاستمرار في توصيل الطلبات في الخدمات اللوجستية للتوصيل الجماعي. ومع ذلك، فإن عامل التقدير (EI)، والفائدة الاقتصادية (EB)، والمخاطر المدركة (PC) ليس لها تأثير كبير. كما أكدت الدراسة من خلال النتائج أن نية البقاء في الوظيفة تتأثر بالفروقات الحفزية بين سائقي التوصيل العرضيين والملتزمين. على الرغم من أن الفائدة الاقتصادية (EB) لا تؤثر بشكل ملحوظ على نية الاستمرار في توصيل الطلبات بشكل مباشر، إلا أنها تؤثر بشكل إيجابي وغير مباشر على سائقي

التوصيل الذكور والملتزمين. ثانياً، من خلال دراستنا، قمنا بتحديد متغيرات التحكم (الجنس ونوع الوظيفة) المؤثرة على استمرارية قبول الطلبات مع العوامل الكمية مثل التعويض والمسافة والوقت في بعض سيناريوهات الاستطلاع لتطوير نموذج توقعي للتنبؤ باحتمالية قبول السائق لطلب معين باستخدام تقنيات التعلم الآلي مثل نماذج التعلم التجميعي (XGBoost, RF, and Soft Voting)، ونماذج التعلم العميق (ANN, GRU, LSTM, and AlexNet)، ونماذج التعلم الآلي التقليدية (DT, SVM, and LR)، حيث تم تقييم أدائها عبر معايير متعددة مثل معيار الدقة الشاملة (Accuracy)، و نسبة الدقة (Precision)، و مؤشر الاستدعاء (Recall)، ودرجة (F1-score). لقد أظهرت نماذج التعلم التجميعي والعميق أداءً متميزاً، حيث حقق كل من XGBoost و ANN أعلى معدلات الدقة الشاملة (Accuracy) بلغت 91.06% وبلغت نسبة الدقة (precision) بحوالي 89.97%. أما بالنسبة لقياس مؤشر الاستدعاء (recall) بلغت كل من XGBoost بمقدار 96.70%، و ANN بحوالي 93.09%. بالمثل أشارت نتائج درجة (F1-score) في XGBoost بمقدار 91.43%، و ANN بمقدار 91.46%. إضافة لذلك أظهرت نتائج تحليل الحساسية - بإضافة بيانات أكثر - الأداء الفائق لنموذج RF و XGBoost حقق نموذجا RF و XGBoost دقة شاملة (Accuracy) بنسبة 95.60% و 95.49%، ودقة التنبؤ (Precision) بنسبة 95.79% و 95.74%، واستدعاء (Recall) بنسبة 95.45% و 96.35%، وقيم (F1-score) بنسبة 95.63% و 95.50% على التوالي. تعكس هذه النتائج مستوى الإتقان والفعالية العالية للنماذج المستخدمة في الدراسة، مما يؤكد على قوة وموثوقية تقنيات التعلم الآلي في التنبؤ والتصنيف الدقيق. كما تسهم الدراسة على الدور الحيوي لاختيار السمات وضبط النماذج في تحقيق أداء تنبؤي قوي، وتحسين العمليات وفقاً للمتطلبات اللوجستية المتغيرة مع الوقت، مما يعزز كفاءة فعالية منصات الخدمات اللوجستية للتوصيل الجماعي في جذب والاحتفاظ بالسائقين.

CHAPTER 1

INTRODUCTION

1.1 Crowdsourced in Last Mile Delivery

The concept of last-mile delivery with crowdsourcing has gained popularity, primarily due to the exponential growth of e-commerce and the substantial expenses involved in the final phase of the supply chain. The last-mile delivery segment plays a pivotal role in the competitiveness of e-commerce enterprises, as it constitutes a significant portion of the overall delivery costs. With the escalating demand for deliveries, there is an increasing necessity for environmentally sustainable solutions to tackle the additional mileage and vehicle emissions [1].

One pioneering solution to this challenge is crowdsourcing, defined as “the practice of obtaining needed services, tasks, or materials by requesting contributions from a large group of people and especially from the online community rather than from traditional employees or suppliers [2]”. Another emerging concept is crowdshipping, where individuals help deliver packages to online customers on their way, thus reducing costs, easing traffic, and relieving professional delivery fleets' workload. Kim et al. [3] contributed to this concept by examining the incorporation of crowdsourcing into traditional delivery systems within last-mile logistics.

Recently, there has been a notable expansion of crowdsourced delivery companies into the last-mile product delivery sector. This development has the potential to trigger a competitive struggle between traditional delivery firms and crowdsourced delivery companies, specifically over control of the last-mile delivery market. While this issue has created a lot of debate [4], it has not become an area of focus in much of the general academic literature.

Conventional home delivery services in cities bring along many opportunities for consumers and courier companies and, at the same time, make some challenges possible. One of the major concerns is the increase in traffic jams and the limited number of parking lots which give problems in improving delivery efficiency. The demand explosion for last-mile delivery has also pushed courier companies to meet tight delivery windows while making their deliveries prompt and reliable. Therefore, innovative solutions to handle such challenges have come up to include crowdsourcing delivery systems [5, 6]. Employing crowdsourcing thereby stands in the way of obstructions that can be overcome in enabling home delivery to thrive in urban areas in line with the changing trends in the demand for commodities by consumers and businesses.

The adoption of crowdsourced logistics in last-mile delivery greatly benefits logistics service providers and e-commerce organizations in Saudi Arabia. This innovative approach offers numerous benefits, including improved efficiency and cost-effectiveness. However, it is crucial for companies to carefully consider courier or courier acceptance as they adopt this new model. It is important to note that the widespread use of delivery services in urban areas of Saudi Arabia is currently limited. Despite this challenge, the Saudi Arabian market for last-mile delivery services demonstrated significant growth, worth \$285.3 million in

2020. Projections indicate that it will expand to reach \$520.9 million by 2030, exhibiting a compound annual growth rate (CAGR) of 6.3% from 2021 to 2030 [7]. Over half of the total shipping expenses are attributed to last-mile delivery, highlighting its significance in the logistics industry. The COVID-19 pandemic has positively impacted online shopping in Saudi Arabia, leading to a remarkable 40% growth from 2015 to 2020. As a result, there has been a significant surge in online shopping, with approximately 77% of customers in Saudi Arabia now choosing to shop online since the pandemic outbreak [7].

In Saudi Arabia, a myriad of delivery platforms, such as Swoosh, Mrsool, Fetchr, Hunger Station, Uber Eats, Jahez, The Chefz, Siwar, Koinz, Carriage, Careem Now, Talbat, McDelivery Saudi, and others, collaboratively facilitates streamlined access to a diverse array of products. This collaborative and innovative spirit embedded within these platforms significantly contributes to enhancing the convenience and accessibility of services for the people of Saudi Arabia. Crucially, the success of these delivery platforms, especially in crowdsourced last-mile delivery, relies on the readiness of individuals, known as crowdworkers (couriers), to accept delivery requests. Recognizing the factors that influence couriers' acceptance becomes pivotal for optimizing the entire crowdsourced last-mile delivery process.

Several factors play a role in couriers' decision-making. The first one is the monetary incentive. Couriers want to consider what kind of compensation is offered for delivery services, including variables such as distance to cover, time needed for the delivery, additional fees, and even bonuses. Higher compensation can attract more couriers. Key elements considered by couriers are convenience and flexibility. Since couriers tend to be private individuals already on the move, they are always ready to accept delivery requests

that coincide with their trips or occur within an easily accessible area. This openness to the freedom of choice on both time and location of delivery requests is a feature of crowdsourced last-mile delivery appealing to potential couriers. They also consider factors that matter for one's safety and security. Delivery jobs are evaluated by the credibility and reputation of the crowdsourced logistics, the nature of the goods that entail the delivery, and the risk that the delivery assignment bears. Trusting that the environment is safe and secure raises the rate of couriers' acceptance.

The couriers' acceptance of tasks is of paramount importance in the context of crowdsourced delivery solutions. While there is substantial interest in same-day delivery for online shopping, most consumers still favor the most economical home delivery option [8]. By using occasional couriers and individuals willing to contribute, crowdsourced delivery can effectively meet market demands, potentially resulting in cost reductions for the company that can be passed on to consumers. It also allows for same-day delivery by tapping into in-store customers as immediate delivery resources. Notably, several major companies like Amazon and DHL have ventured into the realm of crowdsourced delivery services. In [9], the authors explored the idea of using physical stores to recruit potential couriers for same-day delivery, and DHL has also experimented with crowdsourced deliveries by leveraging existing traffic flows and establishing a platform for recipients to set delivery conditions.

Similarly, the rapid development and growing use of mobile and wireless communication technologies have opened new horizons for innovative, cost-effective, and environmentally friendly solutions in logistics and delivery [10]. Among sharing economy models, crowdsourcing stands out as the most promising, enabling human resources and logistical

potential through smartphone applications and online platforms [11]. Various platforms facilitate these connections, with regulations differing by location. Crowdsourced shipping, also known as community-based delivery, presents a new and innovative logistics and shipping management method. This model leverages the collective strength of communities or networks to transport products, often bypassing traditional courier services or postal systems. The growing interest in this concept is driven by the flourishing sharing economy and technological advancements that enhance connectivity and cooperation. Crowdsourcing has garnered significant attention in both academic and business fields, as its potential to optimize last-mile delivery while reducing overall operational costs makes it an increasingly attractive solution in the evolving logistics and delivery landscape.

While crowdsourced last-mile delivery offers significant advantages such as cost-effective delivery, it also brings challenges, including quality assurance, regulations, trust-building, fair compensation, and adapting to demand. As a result, understanding variables of incentives, autonomy and perceived concerns is necessary for courier retention and service quality improvement. Platform research on these factors will help improve completion rates, reduce delivery times, and particularly attract high-quality courier service providers to achieve balanced operations and customer satisfaction. This research aims to innovate a new viewpoint that can resolve these problems and provide solutions integrating society into economic growth via the more general technology development process. Despite advancements, there remains a gap in understanding how factors like flexibility, incentives, and perceived concerns affect global courier participation, particularly in the Saudi context.

On the other hand, recent studies such as Fessler et al. [12], Upadhyay et al. [13], Liu et al. [14], Nguyen et al. [15], and Karli et al. [16] have concentrated on the potential benefits

that influence couriers' willingness to participate, however, four critical areas have received less attention: (i) distinguishing between couriers' continued participation intention and their initial participation intention (ii) investigating the impact of perceived concerns, (iii) testing the effects of control variables, such as job type, on participation behaviour, and (iv) integrating technological factors within the study framework, such as effort expectancy and hedonic motivation. This highlights the need for this study to address these gaps and enhance our understanding of the factors influencing courier participation in the crowdsourced logistics sector.

In conclusion, expanding crowdsourced delivery companies into providing the last-mile is a paradigm for effective and low-cost delivery services to the market. In this regard, courier perceptions must provide for effective crowdsourced last-mile delivery.

1.2 Factors influencing the continued participation of individuals as crowdsourcing couriers.

Crowdsourcing has gained immense popularity in recent years within the delivery and transportation services. Sociodemographic variables are one of the main variables influencing people's continued desire to participate as crowdsourcing couriers. According to Le and Ukkusuri [6], Socio-demographic variables influence people's desire to participate in crowd-sourcing driving. The primary variables that may influence a person's choice to involve are gender, age, occupation, ethnicity, income, and level of education. One's level of education may make them desire to participate as a crowdsourcing courier because the person is attracted by the financial rewards and the flexibility of crowdsourcing driving. One's level of education may make them desire to participate as a crowdsourcing

courier because the person is attracted by the financial rewards and the flexibility of crowdsourcing driving. The experience with shipment of parcels is also a variable that affects people's desire to participate as crowdsourced couriers. A person that has ever transferred items can be more attracted to join as crowdsourced couriers because they have the necessary experience and the required skill.

For a better understanding of the acceptance of participants into crowdsourcing, an analysis of the different factors that could play in their decision in the delivery process is necessary. On the broader analysis that people can find in any determinants of courier acceptance from the supply side was performed by Ermagun and Stathopoulos [17]. In their work, multiple factors determining the likelihood of courier acceptance into crowdsourcing platform, which is: Resource and capability availability: "A courier is more likely to accept crowdsourcing when adequate resources, like a vehicle and spare time, are available." Trust and reputation: "Couriers will be more likely to accept crowdsourcing if they trust the platform or the organization mediating the deliveries and if they have goodwill in the crowdsourcing courier community." Rewards and incentives: "Couriers are more likely to accept crowdsourcing if they are offered attractive rewards or incentives for their participation, like monetary compensations and bonus rewards." Ease of participation: "Couriers are more likely to accept crowdsourcing if the process or participation as a crowdsourcing courier is easy and straightforward." In addition, in the work of Le and Ukkusuri [6], it was found out that three key factors influence the acceptance of couriers in crowdsourcing, and they include the exploitation of their social networks, their experience in freight delivery, and their sociodemographic factors which refer to the

features of a population, which includes factors like age, gender, income, and education, and used to describe a population.

Chi et al. [18] found that the receiving of recognition by an organization or community is a significant motivator for the involvement of individuals in crowdshipping. This was again quite decisively proven by Lin et al. [19]. This is based on the concept of social validation, where man finds his motivation and worthiness in belonging to a group or community that is being recognized for a certain behavior. Another study in the same field was conducted by Nguyen et al. [20], in which he studied the influence of crowdshippers' intentions to continue participating in the last mile delivery, while the moderating influence of employment status was also studied. Demographics play a significant role because of the significant impact that socio-demographic characteristics have on the acceptance of couriers by the people since people of a certain socio-demographic profile will be more amenable to taking up crowdsourcing [19]. For instance, tech-socially-savvy and connected youth may have higher rates of acceptance than people who are from the older generations. Freight transport experience: having a prior knowledge of the freight transport business can make the crowdsourcing activities of freight easier because of one's familiarity with the domain; in short, experience in the domain helps a person gain confidence. Finally, the factor of social media also plays a role in courier acceptance.

Our study proposes an integrated model (SETM-UTAUT2) that integrates the Social Exchange Theory Model (SETM) [21, 22] and extending the Unified Theory of Acceptance and Use of Technology (UTAUT2) [23] More precisely, from SETM, we utilize esteem influence (EI), economic benefit(EB), work autonomy (WA), and perceived

concerns (PC), while from UTAUT2, we incorporate effort expectancy (EE) and hedonic motivation (HM). This integrated model investigates key factors influencing crowdsourced couriers' continuing participation in last-mile delivery. Through SETM, we aim to predict couriers' intention to stay with delivery by analyzing the main factors that influence them, recognizing its significance in workforce development for logistics businesses. We hypothesize that the couriers' intention to stay is a function of perceived benefits and costs. While benefits are identified with monetary (economic) benefits, freedom of work (work autonomy), and esteem influence, the costs include perceived concerns. We further apply the UTAUT2 model in examining the factors that influence couriers' intention to accept a delivery task, and it comprises performance expectancy (perceived esteem influence of the crowdsourcing platform), effort expectancy (perceived ease of using the platform), social influence (impact of others' opinion), facilitating conditions (availability of resources), and hedonic motivation (enjoyment and pleasure derived from using the platform). It is important to note that the performance expectancy and the work autonomy are related concepts, and both are considered under the SETM framework. Social influence, on the other hand, was not included in our study because we believe that it is adequately captured by the esteem influence factor in the SETM framework. While facilitating conditions such as smartphones, cars, and navigation systems were not considered in our study, we believe that they are not relevant for couriers' continued participation in crowdsourcing last-mile delivery, as smartphones and the necessary knowledge to use the crowdsourcing platform are already widely available. Consequently, these factors are unlikely to influence couriers' decisions to continue or discontinue working in this field. Additionally, this study investigates the moderating role of demographic variables, such as gender, age, occupation,

income, and type of delivery task, on the constituents influencing the participation of the couriers in crowdsource delivery.

1.3 Prediction Model of courier's acceptance probability of delivery tasks.

Predicting a courier's acceptance of delivery tasks in crowdsourced last-mile delivery is a complex study topic that requires consideration of multiple variables [24]. These factors include the location, final stop, initial trip departure time, and final arrival time of every courier tasked with every delivery. Other factors also at play include the distance of the delivery request, compensation, and the current workload of the courier. Recent studies encourage platforms to incorporate probabilistic acceptance models that account for individual couriers' diverse acceptance behaviors, impacted by variables such as delivery distance, compensation, and geographical features, to improve order dispatch efficiency and client satisfaction [25, 26]. Detailed predictive models can be developed to estimate the probability of a courier accepting a particular delivery task, including classification and regression algorithms. The objective of the models is to predict the likelihood of couriers accepting a delivery task, sensitive to delivery platforms with planning to balance operations and contribute to service efficiency enhancement.

Another illustrative example of a predictive model is the agent-based simulation model by Shen et al. [27], who investigated what factors determine performances in the context of crowdsourced last-mile delivery. In their study, the effect of a larger supply-to-demand

ratio was contingent on the share of processed packages. Consequently, the delivered package percentage increased while the utilization of crowdsourcing couriers decreased. Another approach to predict courier acceptance is the stochastic model proposed by Gdowska et al. [28], in which the reasoning criteria between crowdsourcing workers and delivery duties were considered. It is possible to infer the likelihood of courier acceptance if we consider the preferences of couriers, their availability and location, and characteristics of the delivery task, such as distance and urgency. Punel and Stathopoulos [29] investigated that different attributes influence the acceptability and preferences for crowdsourcing delivery through a similar study using stated choice experiments. Likewise, they indicated that the preferences for goods delivery are determined by attributes that affect the acceptance of delivering a crowdsourcing request by occasional couriers. For example, the participant's choice to courier in the crowdsourcing delivery can be due to sociodemographic characteristics such as age, gender, and income level. Among the studies conducted and reported detailed findings is that crowdsourcing users strongly believe in its environmental benefits. Therefore, it can be hypothesized that all couriers with a high probabilistic association with the acceptance of crowdsourcing delivery requests are more environmentally conscious.

Based on the abovementioned factors, a proper connection between demographic courier variables and their delivery task characteristics is important to predict the likelihood of couriers' acceptance. This work employs various machine learning techniques to predict courier acceptance of a delivery task and assesses the accuracy of predictions against actual data. We used models such as Logistic Regression (LR), Random Forest (RF), Artificial Neural Networks (ANN), Decision Tree (DT), Long Short-Term Memory (LSTM),

Support Vector Machine (SVM), Extreme Gradient Boosting (XGBoost), Gated Recurrent Unit (GRU), AlexNet, and Soft Voting. By Creating an effective connection with the local community, couriers are more likely to accept delivery assignments in specific areas or neighborhoods, ensuring a reliable supply of couriers familiar with local routes and customer preferences. Further, considering a courier's prior successful interactions with the crowdsourced delivery platform adds another layer of influence on their acceptance of new tasks. These various elements collectively contribute to optimizing the efficiency and effectiveness of the crowdsourced delivery system.

1.4 Problem Statement

The problem addressed in this research is identifying key factors influencing (i) the willingness of couriers to continue participating in crowdsourced delivery and (ii) the courier acceptance of delivery tasks in crowdsourced delivery. While crowdsourcing platforms heavily rely on a pool of couriers to accept and complete delivery tasks, there is a lack of comprehensive studies examining the specific attributes that influence courier acceptance behavior and predict the acceptance probability. Understanding these factors is crucial for optimizing and matching orders to couriers and ensuring efficient and reliable delivery operations. Therefore, there is a need to investigate and predict the factors that drive participant acceptance in crowdsourced delivery systems, ultimately improving the overall performance of such platforms. In this research, we provide the subsequent four research questions:

1. What are the factors influencing individuals' continued participation as couriers in crowdsourcing logistics?

The primary research question investigates the factors that influence couriers' willingness to continue participating in crowdsourcing logistics by evaluating benefits such as flexible schedules, esteem influence, enjoyment incentives, financial incentives, and convenience against associated costs. Various other factors mentioned in the literature play significant roles in shaping decisions and contributing to overall satisfaction and sustained engagement in the logistics network.

2. What are the key factors influencing individuals' continued participation as couriers in crowdsourcing logistics in Saudi Arabia?

Our second research question seeks to unveil the key factors from the exhaustive list found in the previous question that influence individuals' decision to persist as couriers. By addressing this question, we aim to shed light on crowdworker retention's intricacies in Saudi Arabia's last-mile delivery. Building on our exploration of the factors influencing courier acceptance, we focus on the two following research questions:

3. How does the model enhance courier engagement and operational efficiency in crowdsourcing logistics by considering compensation, delivery time, distance, and control variables?

The proposed integrated model plays a pivotal role in advancing our comprehension of the factors influencing couriers' decisions to sustain their involvement in crowdsourcing logistics. The model offers a comprehensive framework by consolidating diverse variables and considering aspects such as compensation mechanisms, delivery time, delivery

distance, and couriers' control variables. This integrated approach enriches our understanding and provides practical insights for stakeholders aiming to optimize courier engagement and enhance the overall efficiency of crowdsourcing logistics operations.

4. How can a predictive model be developed to determine the likelihood of a courier accepting a particular order in crowdsourcing logistics?

The fourth research question relates to the ML-based predictive model that we develop. The aim is to build a model that predicts a courier's probability of accepting a specific order in crowdsourcing logistics. The model will contain several attributes related to delivery and consider them an important contribution to our study.

1.5 Research Motivation

1.5.1 Managerial Motivation

The results of implementing crowdsourcing concepts have been promisingly productive in the case of several pilot projects as well as for several entrepreneurs. For example, local food delivering service in the United States, Postmates, has been successfully showing the application of crowdsourcing [30]. A similar consumer-to-consumer service within the Netherlands has also been successful in implementing the crowdsourcing concepts, especially for peer-to-peer deliveries [31]. Amazon, an established company in the market, has come up with its model, the Amazon Flex concept, providing services with the application of crowdsourcing [32]. Thus, all these cases help to highlight the usefulness of the implementation of the crowdsourcing concept in the logistics supply chain.

The ability to save costs compared to traditional courier, express, and parcel services is one of the major benefits of crowdsourcing. Since crowdsourcing eliminates the expensive infrastructure costs, the savings associated with it support the cost advantage of crowdsourcing companies over traditional logistics providers [5]. This allows crowdsourcing logistics providers to provide last-mile delivery services at a cheaper rate and thus be preferred for some businesses—neighborhood stores, grocery shops, or food places, especially in urban areas [33, 34]. At the same time, crowdsourcing can lead to the retention of consumers who prefer e-commerce to visiting retail stores because of lower travel lengths and costs of services of traditional delivery companies [34]. Crowdsourcing has great potential to make sustainable transportation a reality using existing trips, thereby minimizing the environmental impact on the road of extra delivery vehicles—according to road [6, 35]. Thereby, an adequate number of people will be motivated to participate as crowdsourcing participants. Understanding the motivation of the crowdsourcing participants is very essential to create the strategy of the crowdsourcing system, which would be in line with the expectation and the need of the participants in last-mile delivery, as reported by [36], and [37]. This could help in obtaining the critical mass required for the realization of the success of crowdsourcing in last-mile delivery.

1.5.2 Academic Motivation

Although most research papers on crowdsourcing have studied business models and scalability, there exists a scarcity of relevant papers in the domain of crowdsourcing in on-demand last-mile delivery. Performing limited number of papers are the behavior of couriers, willingness of potential crowdsourcing couriers, and the shipping conditions associated with it. There are relatively few papers published which discuss the willingness

of potential crowdsourcing couriers and associated shipping conditions. Similarly, there is a significant lack in the literature on the behavior of related stakeholders. Currently, there is a minimum lack of studies on motivational factors for the engagement of crowdsourcing couriers. However, benefits and risk factors associated with the behavior, and the relationship between habits, lifestyle, and the willingness of couriers to participate in crowdsourcing, require further study. Most of the studies pertain to the demographic factors of potential crowdsourcing participants. However, it remains unclear whether and which benefits and risk factors related to couriers affect the willingness of couriers to participate in crowdsourcing.

The research line addresses the importance of explaining courier acceptance within the context of crowdsourced, on-demand, last-mile delivery services. The research intends to work on the development of methodology capable of predicting courier acceptance behavior, given the features. By understanding the factors that influence courier acceptance, researchers aim to improve the efficiency and effectiveness of crowdsourced delivery systems.

The research will focus on acceptance factors of crowdsourcing and the development of a predictive model using ML techniques. This approach is novel and contributes to literature by identifying specific attributes that have not been extensively studied before. This study aims to enhance the understanding of the importance of these attributes that influence the courier in accepting or rejecting tasks.

1.6 Research Objective

In the following, we shall provide the main three objectives of our research:

1. The primary objective of this thesis is to identify the factors influencing individuals' continued participation as couriers in crowdsourcing logistics.
2. The secondary objective is to propose a model (SETM-UTAUT2) that integrates SETM and UTAUT2 to investigate the significant factors influencing couriers' participation and retention in Saudi Arabia using surveys and analyzed by SPSS Amos 26.0. The model gathers benefits such as financial incentives, enjoyment incentives, esteem influence, effort expectancy, and flexible schedules against associated costs such as perceived concerns.
3. The third objective is to investigate specific attributes for developing a model to predict the probability of courier acceptance, using ML techniques, for a particular delivery task in crowdsourcing logistics in Saudia Arabia.

1.7 Contributions of the Research

Our contributions are as follows:

1. Provide a comprehensive literature review on understanding the factors that influence the continued participation of crowdsourcing couriers, as well as review and determine the existing research gap for Stated Preference (SP) factors that influence the acceptance probability of delivery tasks in crowdsourcing last-mile delivery.

2. Propose a model that integrates the Social Exchange Theory Model (SETM) and the extended Unified Theory of Acceptance and Use of Technology (UTAUT2) to explore factors influencing couriers' intentions to continue working in crowdsourcing last-mile delivery by employing SPSS Amos 26.0.
3. Identify the key quantitative factors such as compensation, driving distance, time, and courier' control for developing a predictive model of the probability of courier acceptance for a particular delivery task in crowdsourcing logistics.
4. We utilize a binomial logit model to identify the main quantitative and control factors that influence the acceptance of delivery tasks in crowdsourcing and compare the performance of the actual model with predictive ML models.

In summary, our research provides a valuable contribution to the understanding of factors effecting couriers' willing to continue participating in crowdsourcing delivery, and it evaluates benefits s against costs to enhance overall satisfaction and engagement. Focused on crowdsourcing logistics in Saudi Arabia, the research provides insights into couriers' decisions in this region. The model can be used by crowdsourcing platforms to improve order completion rates and reduce the delivery time. Furthermore, our research findings would identify the crowdsourcing platforms that are more effective in attracting and retaining couriers. Finally, it is crucial for optimizing task allocation and ensuring efficient delivery operations.

1.8 Thesis Outline

The remainder of this research is structured into several chapters. The second chapter introduces the conceptual background by examining prior studies related to the factors affecting continuous courier participation of delivery requests within the context of crowdsourced last-mile delivery. Additionally, it identifies a research gap that this study aims to address. It also outlines the establishment of the literature review and the research objective of predicting couriers' acceptance and investigating the impact of various factors on courier behavior. The third chapter outlines the theoretical foundation of the research model. Furthermore, it provides a detailed overview of the conceptual research model and the development of hypotheses and outlines the research methodology related to the factors influencing continuous courier participation. The fourth chapter describes the development of a model, and the research methodology designed to predict the likelihood of acceptance for delivery tasks, ensuring a balance between theory and practical aspects. The fifth chapter presents the data analysis and discussion, exploring practical implications alongside theoretical insights. The final chapter summarizes the main research findings, encompassing theoretical and practical contributions, limitations, and suggestions for future research.

CHAPTER 2

LITERATURE REVIEW

Limited studies focus on the models for individuals' continued participation as couriers in crowdsourced last-mile delivery. In Section 2.1, we will review and determine the research gap this study aims to fill based on the review related to crowdsourcing in last-mile delivery. Section 2.2 focuses first on the factors affecting whether couriers choose to continue participating in such delivery services, then explains SETM-UTAUT2 model, analyzing crucial elements influencing couriers' participation benefits and costs. Finally, Section 2.3 reviews the models on the probability of couriers accepting the delivery tasks assigned by the platform.

2.1 Crowdsourced last mile delivery

One of the most significant and challenging aspects of logistics is the last mile delivery, which is the final step in the supply chain. Recent years have seen the development of crowdsourcing, a decentralized method that uses the combined efforts of many individuals, or a crowd, to complete delivery tasks. Recent literature on Crowdsourced deliveries discusses various aspects of the phenomenon including the associated challenges. Several studies explore different logistical models including the involvement of public transport [38-41], transshipments [42], and routing problems [43, 44]. Whereas many studies are highly focused on technical, operational, and sustainability perspectives and highlight several operational challenges like operational costs and pay structures [3, 42, 45, 46] [3,

42, 45, 46], online scheduling [47], supply-demand balance [48], algorithm development for ride sharing [49], socio-environmental impact of crowdsourced shipping [39], and overall sustainability [50]. More research is needed to study the impact of crowdsourced delivery on the economy [41], the emergence of new delivery modes [51], and pricing [52]. All latter studies do not consider the behavioral aspects. Nevertheless, there is a vast body of literature focuses on participants behaviors [12, 13, 39, 44, 53]. The participants' behavior in crowdsourced delivery can be divided into two main eras. Early studies are focused on participation behavior in crowdsourced delivery [54-56]. Recently, the focus has shifted towards participants' continuing behavior in crowdsourced delivery [14, 57, 58]. Some of these studies are geography-specific, such as studies representing the Chinese market [21, 59, 60], the Vietnamese market [58], the Dutch market [61], and the Danish market [12]. The reason behind geography-specific studies is that the crowdsourced delivery networks are not global yet, and the behaviors of the network participants are impacted by several factors, including domestic culture, domestic infrastructure, and demographics in general. There are very few studies that attempt to explore crowdsourced delivery in Saudi Arabia, for instance, Alharbi et al. [62] explores the generic benefits and challenges of crowdsourced logistics, while Bajec and Tuljak-Suban [63] proposes the strategic approach towards crowdsourced last-mile logistics. Given the significant potential of crowdsourced delivery in Saudi Arabia, which is still in its developmental phase, and the limited research on the behavioral aspects, particularly couriers' intention to continue participating in crowdsourced deliveries, it is crucial to explore this market further. Factors influencing the continuation intention can vary greatly across different geographical regions. Therefore, it is essential to identify and understand the specific factors driving user

engagement and continued participation in Saudi Arabia's crowdsourced delivery ecosystem. By investigating these factors, we can obtain benefit insights that could improve the sustainability and growth of crowdshipping platforms in the region and contribute to Vision 2030. Literature on the continuation behaviors infers six different factors influencing the behaviors that are summarized in [Table 1](#). This study intends to include all these six factors identified by the previous studies as their presence in any culture and geography has a varying intensity. Therefore, our study will be the first study that considers all six factors.

The purpose of this examination of the literature is to give an overview of the concept of crowdsourced last-mile delivery, as well as the evaluation focuses on the elements influencing people's acceptance to continue working as crowdsourced delivery couriers and the likelihood of an acceptance model for people to continue working as couriers as referred in [Table 1](#). The acceptance probability model is the probability of a courier accepting a delivery assignment. It is a function of parameters such as money or reward value, distance travelled, time spent traveling, and the courier's preferences, as indicated in [Table 2](#). The review reflects the gaps in the research and the existing models and methodologies and presents relevant studies on these aspects.

The application of crowdsourcing in last-mile delivery is an area of intense investigation. Devari et al. [64] explored a new method using buddy networks, where customers are paired with friends or acquaintances willing to deliver their online orders. This method is often called social network-supported last-mile delivery. Huang and Ardiansyah [65] found that crowdsourcing can reduce costs and increase operational efficiency in last-mile delivery. Order assignment and information-sharing strategies directly impact delivery

efficiency because couriers are in high demand [66]. This study examines how these strategies affect couriers' perceptions of fairness and their willingness to participate consistently.

Kafle et al. [67] described a crowdsourcing system for managing urban express parcel exchanges and delivery. They highlighted the potential benefits of crowdsourcing for last-mile transportation, such as faster and cheaper deliveries. Researchers have also identified potential drawbacks and solutions when using crowdsourcing in last-mile delivery. For instance, Yuen et al. [68] addressed the issue of last-mile package pickup and drop-off in cities. They proposed a hierarchical incentive system to motivate people to take on last-mile delivery tasks. This system aims to address trust, security, and incentive issues associated with crowdsourcing. Providing rewards for those involved in delivery activities encourages more people to participate in last-mile logistics.

2.2 Review of research on continued couriers' participation behavior in crowdsourcing

Work specifically related to last-mile delivery crowdsourcing for on-demand services is scant. Existing studies have mainly addressed crowdsourcing business models and scalability issues, and there is no comprehensive study that explains the factors that drive the couriers' willingness to continue working in last-mile delivery, given the sending condition. Several current trends and the available literature suggest that more research should be done into the benefits and risk factors (cost) of using crowdsourcing for last-mile delivery [20], as well as the potential associations between the habits, lifestyle, and engagement in crowdsourcing of couriers. Most found studies focus largely on the

demographic factors of potential crowdsourcing participants. While it remains unclear which benefits and risk factors influence couriers' willingness to continue participating in crowdsourcing, this section reviews the literature to identify the factors impacting couriers' involvement in last-mile delivery crowdsourcing.

In recent years, crowdsourcing has gained popularity in different businesses, particularly in transportation and delivery services. The key factors that have a significant effect on the acceptance of individuals to work as couriers may be sociodemographic factors, including gender, age, ethnicity, income, and education. On the other hand, Ermagun and Stathopoulos [17] mentioned that there are several key factors affecting the supply side of the courier: availability of resources and capabilities, trust and reputation, rewards and incentives, and ease of participation. Furthermore, the three most important factors affecting the acceptance of couriers, as elaborated by Le and Ukkusuri [6], include social networking utilization, freight delivery experience, and sociodemographic variables.

Liang et al. [69] referred to subjective norms, perceived behavioral control, and willingness to crowdworkers positively affects crowdworkers' intention to continue. Lin et al. [19] revealed that among other motivating reasons for engagement of couriers, recognition from an organization or community matters. Besides, [70] conducted a study on crowdsourcing initiatives based on Social Exchange Theory and showed that seeking identity disclosure & status leads to a positive influence on motivation. This finding will be helpful in improving crowdsourcing participation. Nguyen et al. [20] found that economic benefits and work autonomy positively impact courier's intention; on the other hand, job stress and payment risk, negatively affect customer's interest. Demographic information also has an impact on courier acceptance. Young, tech-savvy, and experienced individuals will have a

higher likelihood of accepting courier assignments. Besides this, social media use will also affect courier acceptance. Wang et al. [71] conducted a study to explain the impact of fresh food sales acceptance in e-commerce by individuals based on structural equation models, which helps understand shopping behavior. The study will show us how participants in e-commerce behave, and, thus, it can also influence the way couriers continue participating in a crowd-sourced environment. Kafle et al. [67] presented a system-enabled by crowdsourcing to do urban parcel delivery, allowing delivery to be faster and cheaper. Yuen et al. [68] conducted research on the issues related to last-mile package pickup and drop-off in cities. They recommend a hierarchical incentive system by crowdsourcing to create motivation among people to opt for last-mile delivery. This system achieved the goal of solving trust, security, and incentive matters involved in using crowdsourcing to get last-mile delivery done. People are more motivated to be involved and assisted in the last-mile logistics if rewards can be given for being part of the delivery activities.

Huang et al. [59] have shown that financial rewards and trust can positively influence employees' motivation and used the Push-Pull-Mooring (PPM) theory on participation, with participation satisfaction and blockers on entering the task as negative. A theoretical model has been proposed by Zhang [60] that uses intrinsic and extrinsic motivation, participation satisfaction, subjective norms, perceived behavior control, will to participate, and habit. The most salient variables are perceived behavior control, habit, and Willingness to Intend and Continue Participation (WICP). Model integrated both the TPB and PAM-ISC models, they used data that was gathered from a survey of 500 workers. Important limitations of the study must be kept in mind, including the fact that the sample may not be representative of the larger population being studied, and that there may be the exclusion

of external variables that may affect continued participation. They may affect the wider applicability of the findings and should be considered. Buldeo Rai et al. [72] examined crowd logistics and its sustainability implications, identifying 18 characteristics, and evaluating economic, social, and environmental sustainability. They used 42 questionnaires and 11 interviews with logistics practitioners who expressed an interest in using the crowd in their logistics activities. Although the study focuses on the Flanders and Brussels capital region in Belgium, it suggested broader geographical analyses, stakeholder studies, and sustainability impact assessments for the research. [21] studied factors influencing couriers' participation in crowdsourcing, highlighting trust, financial incentives, enhancement of skills, enjoyment, and job autonomy as positive influencers and Loss of knowledge power and cognitive stress as a negative impact on participation. Important limitations of the study must be kept in mind, including the fact that the sample may not be representative of the larger population being studied, and that there may be the exclusion of external variables that may affect continued participation.

This was important to explore since studies into "Continuous participation behavior intention" have been gaining attention in the past years [73]. Continuous participation behavior intention in crowdsourcing is indicated by the interest of an individual to contribute to the company [74] and intention to remain working [75]. At another level, it has been found that subjective value assessment [76], the Theory of Value Expectation [77], Motivation Theory [78, 79] and the Social Identity Theory [55] are the most influential factors in affecting this intention. The mentioned theories thus indicate that participation in a group will greatly influence the intention to continue to do so, thereby influencing their participation in crowdsourcing efforts.

Prior studies mainly focused on the impact of potential benefits on couriers' willingness to participate. However, less attention has been given to three key points: 1) differentiating between couriers the continued participation intention and the participation intention 2) analyzing the effect of cost concerns; and 3) exploring the mediating effect of control variables, such as job type, on participation. 4) incorporating technological dimensions into the study framework, including aspects such as effort expectancy and hedonic motivation. On the one hand, some studies do not address the role of costs in couriers' participation. While, on the other hand, some studies clarify how benefits affect couriers' involvement, they do not as well account for the impact of costs. To fill this gap, we use the Social Exchange Theory Model (SETM) model to understand this issue, as proposed by Blau [22], and Ye and Kankanhalli [21]. The SETM hypotheses are applied here to explain why employees, in our case couriers, keep participating in their jobs, considering both costs and benefits.

2.2.1 Social Exchange Theory Model (SETM)

Social Exchange Theory Model (SETM) considers people's behavior in social situations by incorporating the costs and benefits involved [21, 22]. Individual's decisions, like selecting a job, are based on the cost vs. benefit trade-off [80]. When rules are absent, individuals guess the future outcomes to justify their expected gain [81, 82]. Staying in a job or staying active socially depends on the benefits, like reputation or pleasure [83]. Couriers in the last-mile crowdsourcing would continue to participate if the benefits outweigh the costs [84]. They are also concerned with whether their efforts are appreciated

[85]. The SETM, which suggests that the decision of a person to participate is based on the evaluation of the exchange's benefit-cost when applied, helps to provide a theoretical guide to why couriers participate in crowdsourcing. We draw from the SETM as a general guide of our model, and we adopt it to give a general framework. To offer more specificity, we draw from context-specific literature, mainly from existing research on crowdsourcing. In this way, we achieve comprehensiveness and well-versed dimensions to give a position of why participants, like couriers, invest in crowdsourcing.

2.2.2 Extended Unified Theory of Acceptance and Use of Technology (UTAUT2)

Individual acceptance is significant for successful implementation of new technology. TAM Davis et al. [86] identified that the legitimacy and perfection of information technology in the views of the people are the ones which influence the use of technology. In later studies, Venkatesh et al. [87] found that the facilitating conditions, social impact, and demographic variables are the reasons for adopting technology. The study examined the different theories that are the reason for the formation of UTAUT and how it can be used to information technology in a commercial situation. UTAUT integrates the elements of perceived usefulness (PU) and ease of use (EU) from TAM with the concepts of performance expectancy (PE) and effort expectancy (EE). UTAUT2 [23] is the extension of UTAUT by considering additional factors like social influence, facilitating conditions, hedonic motivation, habit, and price value.

Several other studies have used UTAUT2 to analyze factors affecting participation in various domains, for example, mobile banking services [88] and use of social networks in education [89]. In the present research, the UTAUT2 model is used to study, in its entirety, the factors causing the influence of participation in crowdsourced logistics operations with the desire and effort expectation of couriers. This is motivated by the unique dynamics of the technology adoption procedure. UTAUT2 has not been used in any previous study for the continuous participation intention of couriers in last-mile delivery. We opted to use UTAUT2 since it fits the purpose of studying the acceptance of crowdsourcing by couriers. Thus, effort expectation and hedonic motivation of UTAUT2 are included since such constructs are relevant to courier acceptance in last-mile delivery crowdsourcing. These factors help capture the unique dynamics of technology adoption in this context, while simultaneously addressing other relevant factors through the application of SETM (see [Table 1](#)).

Table 1 Factors influencing couriers' behavior in crowdsourced delivery from prior studies.

Paper	Influencing Factors						Survey outcomes	
	Esteem influence	Monetary (Economic) benefit	Effort(skill) expectancy	Enjoyment (hedonic motivation)	Work autonomy	Perceived concern	Participation behavior	Continued Participation Behavior
Haichao et al. [79]				✓			✓	
Sun et al. [54]	✓	✓				✓	✓	
Boons et al. [55]	✓		✓			✓	✓	
Mladenow et al. [90]		✓		✓		✓	✓	
Liu et al. [91]						✓	✓	
Deng and Joshi [92]					✓		✓	
Ye and Kankanhalli [21]	✓	✓		✓	✓	✓	✓	
Geri et al. [78]	✓	✓					✓	
Buldeo Rai et al. [72]	✓	✓				✓	✓	
Staats et al. [93]	✓						✓	
Blau [22]	✓	✓			✓	✓	✓	
Liang et al. [69]	✓	✓	✓	✓				✓
Blohm et al. [94]		✓					✓	
Gdowska et al. [28]		✓					✓	
Guo et al. [95]	✓	✓	✓			✓	✓	
Zhang [60]	✓	✓		✓				✓
Lin et al. [19]	✓						✓	
Huang et al. [59]		✓		✓	✓	✓		✓
Leung et al. [96]		✓	✓	✓		✓		✓
Karli et al. [16]		✓			✓		✓	
Loan et al. [97]						✓	✓	
Nguyen et al. [58]	✓	✓			✓	✓		✓
Liu et al. [14]	✓	✓			✓	✓	✓	
Xie et al. [57]		✓			✓	✓		✓
Nguyen et al. [15]	✓	✓	✓				✓	
Upadhyay et al. [13]	✓	✓		✓	✓	✓	✓	
Fessler et al. [12]		✓	✓			✓	✓	
Our study	✓	✓	✓	✓	✓	✓		✓

2.3 Probability of couriers' acceptance of delivery tasks as crowdsourced delivery courier.

This section reviews the literature on the acceptance probability of delivery requests in crowdsourced last-mile delivery. This review provides an overview of the crowdsourced last-mile delivery, focusing on factors influencing a courier's decision to accept a delivery, such as monetary reward, distance traveled, time spent traveling, and the courier's preferences, as indicated in [Table 2](#). The aim is to highlight gaps in current research, evaluate existing models and methodologies, and present relevant studies in this area.

Crowdsourced delivery is utilized by on-demand service platforms like Uber, Lyft, Grubhub, and Eat24. These platforms have drastically altered people's views of the potential advantages and benefits of crowd-sourced transportation and shipment, particularly when ordering food Yildiz and Savelsbergh [98]. Many retailers, for instance, are weighing the advantages and disadvantages of incorporating crowdsourced delivery into their channel plans. In such situations, however, there are limited models available to facilitate the examination of capacity for delivery planning, and quality of service, as well as how they communicate. Yildiz and Savelsbergh [98] provided a model that aims to accomplish just that and can answer many fundamental problems in these situations. Using platforms for immediate food delivery as an illustration, they explored the connection between delivery offers acceptance probability and revenue service region, and the advantages of consolidating delivery services from multiple restaurants. Ermagun et al. [99] empirically investigated the matching and delivery processes in a significant crowd-sourced delivery platform. They investigated goods status prediction in crowd-sourced

shipping systems online. In practice, the given models showed promising results in their capacity to accurately anticipate shipping status in real-time. This study looked at the popularity of the scheme of food delivery services via web application by motorbike courier, also known as Go-Food, among Indonesians. The rise of crowd-sourced couriers presents an opportunity to restructure conventional in-house delivery services. Three scenarios that addressed different courier preferences were studied by Tao et al. [100]: guaranteeing a minimum daily order capacity for full-time couriers, establishing a maximum order limit per trip, and modifying the detour proportion for part-time couriers. Their goal was to devise a technique that would enable Online-to-Offline platforms to achieve optimal order distribution and transportation while considering these courier decision patterns. Öztan et al. [101] investigated the connections between stress, peer value, and perceived logistic support in their research on shipping vehicle workers. The research emphasizes how crucial it is that delivery schedules for commercial food ordering systems consider courier safety.

While most research in crowdsourcing focuses on the demand side, there is limited study on the probability of couriers accepting tasks on the supply side. The literature discusses couriers' preferences for various service factors and the influence of crowdsourcing on the acceptance probability of last-mile goods delivery. Punel and Stathopoulos [29] studied the aspects that affect the desires and acceptance of crowdsourcing in various market settings by surveying with stated choice scenarios. The survey incorporates several innovative features, such as courier competency and rating, and enhanced client control over the scheduling of delivery tasks. Preference research shows that speed, cost, dependability, and unique characteristics like tracking and courier good standing are highly preferred. The

impact of an impression of community is minimal on crowdsourcing appeal compared to the element of social communication and innovative searching. In other related study, [102] developed a binomial regression model to analyze supply-side bidding behavior in crowdsourcing services. Afterwards, [99] used the random forest algorithm to forecast performance for the bidding, acceptance, and delivery phases of crowd-shipping in the United States. Their findings highlighted that reward and timing are significant factors in the process. The analysis shows how adjustments in pricing and request timing can enhance delivery probabilities. Their study has limitations, notably the absence of a comparative analysis, relying solely on the application of the Random Forest algorithm to predict shipment status.

Additionally, some research involves creating stated preference survey questionnaires to gather information, as demonstrated by Le and Ukkusuri [6]. They explored the factors influencing senders' choices of shipping services. Their findings indicate that shipping costs, courier rating, tracking, and service timing play significant roles in decision-making, with senders willing to pay more for enhanced services in crowd-shipping for grocery goods. This work employs techniques such as Random Utility Maximization (RUM) and Random Regret Minimization (RRM) for behavioral modeling. Gatta et al. [103] researched the case of crowdsourcing in the Rome metro where services based on Automated Parcel Lockers (APLs) were used as pick-up and drop-off places for delivery tasks. The goal was to estimate the chances for people to become couriers and adopt crowdsourcing services under different service configurations. They used preference surveys in a bid to identify the most critical factors influencing participation from the two perspectives, i.e., the demand and supply side. Data was collected by the research team

using two different questionnaires where the first was handed to 240 Rome consumers and the second was mailed out to 240 metro users. Researchers developed two multinomial logit models to test the likelihood of using crowdsourcing services and participating as couriers. They discovered that the planned service conditions had the greatest influence on these possibilities. Notably, the position of APLs was considered the most important consideration, outweighing compensation. Consumers placed high importance on having control over the demand side's delivery date and time schedule. Furthermore, the study found that the potential supply of crowdsourcing services in Rome outstripped the potential demand.

Marcucci et al. [104] studied the factors that impact the acceptance of individuals to engage as crowd workers and the preferences of potential crowdsourcing customers. They surveyed 200 university students and discovered that 87% were eager to be crowd workers, and 93% were interested in being willing to engage on the demand side. The percentage falls if the package size is not tiny or the payment is less than 5 euros. The study found that factors such as compensation, package size, and communication channels all significantly affected engagement. Gender inequalities were discovered, with women being more likely to be crowdsourcing recipients and males being more likely to be couriers. The average estimated maximum additional travel distance for couriers was 2.4 kilometers. Students are expected to earn an average of 5 to 10 euros for each delivery, which is greater than the average supplied by present initiatives (usually between 2 and 4 euros). The authors proposed that students' inaccurate estimation of the economic gain per delivery is likely due to a misunderstanding of the true purpose of crowdsourcing. Furthermore,

students overlook that excursions are not devoted and, as a result, overestimate the work required to complete the delivery.

Yildiz and Savelsbergh [98] analyzed service coverage and capacity planning issues in on-demand food delivery systems. The researchers explored how the likelihood of accepting delivery tasks affects revenue and the optimal service area sizing. Their findings revealed that as acceptance likelihood and courier unit-time costs decrease, so does the radius of the best service region. The paper also concludes that the benefits of using professional couriers are greater when the acceptance probability of the couriers is low, and the unit income is high. To examine the impact of the acceptance probability on the benefits that accrue when professional couriers are used, the authors conducted simulations in the paper. It was found that rejection rates increase with higher unit revenues and become more pronounced as the distance between drop-off sites longer, reflecting couriers' sensitivity to the perceived effort and time involved. The paper also reports the impact of the firm's couriers' profitability under three conditions: the state of complete acceptance, delivery acceptance not including company couriers, and delivery acceptance including the company couriers. They prove that if the acceptance probability of the delivery is distance-dependent from the point of delivery, then the profit of corporate couriers is a decreasing function of the Occasional Couriers' (OCs) willingness to deliver in the request for customer service.

Devari et al. [64] examined whether social networks can crowdsource last-mile delivery to increase the likelihood of request acceptance in the product shipment. They conducted an online survey of 101 respondents from the US for variables such as friendship level, number of people that participants are in regular communication with, and willingness to

deliver or accept product delivery for environmental reasons or benefits. They analyzed the friend level under which the respondents would be willing to take or deliver the product to friends, other than factors such as monetary benefit and maximum additional time to travel. Based on the survey results, most respondents agreed to help their friends or neighbors by delivering product packages. 60% of the respondents agreed to deliver the packages without expecting any rewards or benefits. However, another 30% agree if they get rewarded by \$5 or more per delivery. More than 80% agreed to add an extra 15 minutes or less for travel time for delivery. It provides a good set of data for the authors to model the probable successful delivery of products in a simulated environment. This innovative approach could reduce last-mile delivery costs and environmental impact.

Le and Ukkusuri [5] conducted an online survey in the US to study the characteristics, attitudes, and behavior of requestors and potential drivers in the crowd shipping market. The results suggest the requestors' demand preference impacts the courier's motive to continue participating and the logistics from the supply side. Moreover, factors such as the platform's ease of use, price norms, and courier incentives are important. The paper considers the couriers' probability acceptance dependent on the socio-demographic criteria and their expectation of fair pay. On the other hand, the requester has anxiety regarding the damage to the product and on-time delivery. Furthermore, [105] have used discrete-continuous models to analyze the attributes related to the willingness to engage and the ability to tolerate travel time. According to the literature on time value, the expected pay expectations of potential crowdsourced driving partners were realistic.

Recent studies have enhanced our understanding of the factors impacting the probability of individuals accepting delivery tasks within crowdsourced last-mile delivery. [39]

analyzed passengers' willingness to participate in crowd-shipping while using public transportation and concluded that young people and people with a positive attitude toward sustainability are more inclined to participate. At the same time, time constraints and low remuneration decrease the likelihood of acceptance. Similarly, Barbosa et al. [106] applied logistic regression based on the influence of compensation and task characteristics; lightweight packages and minimal detours increase the likelihood of acceptance, especially when associated with appealing compensation schemes. Çınar et al. [46] proposed the Compensation-Driven Acceptance Behavior (CAPCAB) model, in which delivery platforms can dynamically adjust the compensation based on task attributes and driver preferences to maximize task acceptance while keeping control of the costs. In related research, Hou [107] investigated the decision-making processes of crowd shippers using a binomial logit model. The study employed stated preference surveys to gather information from shippers in Shanghai, emphasizing the factors that influence their choices, such as age, income, and order-specific compensation. By using this method, the researchers were able to identify the variables that had the most effects on shippers' decisions to accept a delivery tasks. In their study, the best-performing models are both Random Forests and Extreme Gradient Boosting, with the latter yielding more accurate predictions. This paper relies on data from one geographical zone, which may limit the transferability of the findings on other zones or different crowd-sourced delivery configurations. Also, the paper focuses on specific models and may not take into account all potential influencing factors or alternative methods for predictive analysis.

Our study addresses a gap in understanding courier behaviors in Saudi Arabian crowdsourced logistics, where prior research has largely focused on discrete choice and

ML models for predicting transportation behaviors without a direct comparison in our context. Unlike traditional behavior modeling, our empirical approach uses a stated preference survey to evaluate the decision-making of couriers. We assess the effectiveness and computational efficiency of several ML techniques, including LR, ANN, RF, DT, SVM, LSTM, XGBoost, GRU, AlexNet, and Soft Voting. Our findings offer new insights into the factors influencing courier decisions, enhancing participation and platform efficacy in last-mile delivery within Saudi Arabia.

Table 2 Stated Preference (SP) influencing the acceptance probability of delivery attributes in crowdsourcing last mile Delivery.

Paper	Distance	Delivery Time	Time of day	Reward	Weight	Type of service	Courier rating	Compensation	Friendship Levels	Payment method	Control variable	Model Used
Shaheen et al. [108]		✓	✓									Logistic Regression
Devari et al. [64]		✓	✓	✓					✓		✓	Logistic Regression
Punel and Stathopoulos [29]	✓	✓					✓	✓			✓	Multinomial Logit Model, Mixed Logit Model
Miller et al. [109]	✓	✓	✓					✓			✓	Multinomial Logit Model, Mixed Logit Model
Marcucci et al. [104]	✓	✓		✓	✓						✓	Stated preference Model
Ermagun and Stathopoulos [102]	✓	✓	✓		✓	✓		✓			✓	Binary Logit Model
Le and Ukkusuri [5]	✓	✓	✓	✓	✓			✓	✓	✓	✓	stated preference Model
Le and Ukkusuri [6]	✓	✓	✓	✓		✓	✓	✓		✓	✓	RUM, and RRM
Le and Ukkusuri [105]		✓						✓			✓	Binary Logit Model
Ermagun et al. [99]	✓	✓	✓		✓			✓			✓	Random Forest Model
Castillo et al. [110]	✓	✓		✓				✓			✓	Agent-Based Hybrid Simulation
Barbosa et al. [106]	✓			✓	✓							Logistic Regression Model
Hou [107]	✓	✓			✓	✓		✓			✓	Discrete Choice Model
Our study	✓	✓						✓			✓	LR, ANN, RF, DT, SVM, LSTM, XGBoost, GRU, AlexNet, and Soft Voting

CHAPTER 3

DEVELOPMENT MODEL AND METHODOLOGY

3.1 A Continued Couriers' Behavioral Intention Model

3.1.1 Development of a Continued Couriers' Behavioral Intention Model

There is a greater requirement to understand the variables influencing crowdsourcing couriers' continued participation due to the growing popularity of crowdsourcing platforms for last-mile delivery services. This research provides a framework for understanding the factors that impact couriers' behaviors to persist in crowdsourced last-mile delivery. We propose an integrated model that incorporates (SETM) with cost-benefit analysis [21, 22] and (UTAUT2) [23]. Through its integration, we encompass a wider range of aspects pertinent to our research and avoid the models' limitations, offering a more thorough and nuanced comprehension of the topic. In [Figure 1](#), we give an overview of the proposed model.

Recognizing the importance of workforce management for logistics companies, SETM is utilized to investigate the primary features and incentives influencing couriers' decisions to stay in this industry. We theorize that perceived benefits and costs influence couriers' intention to stay. Benefit variables include economic benefit, work autonomy, and esteem influence, While the cost factors encompass concerns at work related to order cancellation, health, security, and environmental risks associated with the use of delivery services. In the context of crowdsourcing last-mile delivery, the UTAUT2 model, which includes

factors such as effort expectancy and hedonic motivation, is applied in conjunction with STEM factors to analyze couriers' participation in the last-mile delivery.

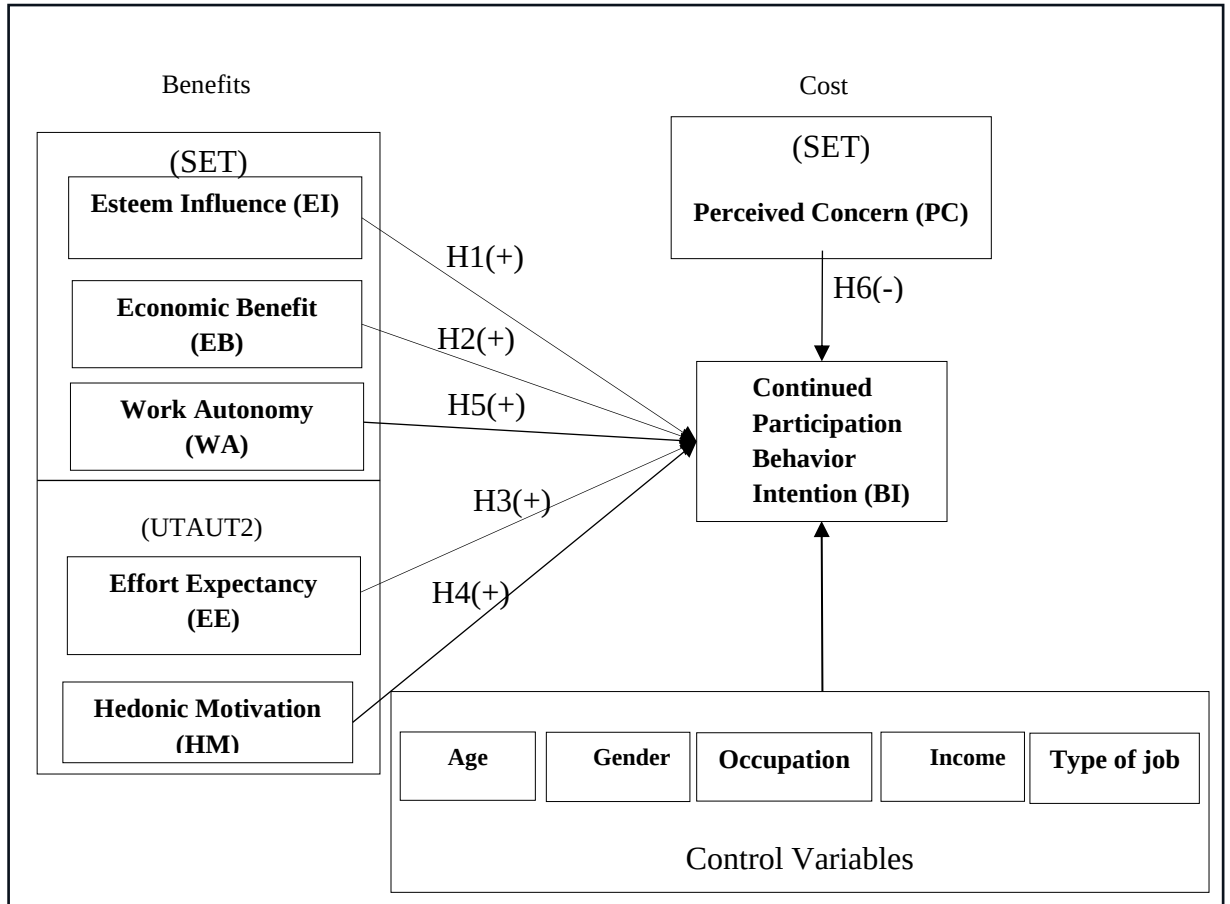


Figure 1 Proposed couriers' continued participation behavior model (SETM-UTAUT2) in crowdsourced last-mile delivery.

In crowdsourcing, performance expectancy refers to the belief that using the crowdsourcing platform will enhance delivery. In contrast, effort expectancy refers to the perceived ease of using the platform. It is important to note that performance expectancy and monetary (economic) benefits are related concepts [95], and both are considered under the SETM framework. Social influence captures the impact of others' opinions on an

individual's decision to accept delivery tasks [78, 111], while facilitating conditions refer to the availability of resources and infrastructure that support platform usage. Our study did not include social influence because we believe that the esteem influence factor in the SET framework adequately captures it. Hedonic motivation highlights the enjoyment [15, 58-60, 69] and pleasure derived from using the platform. While facilitating conditions such as (smartphones, cars, and mobile communication) were not considered in our study as we believe that they are widely available enabling factors and are not determinant of couriers' continued participation in crowdsourcing last-mile delivery. The Habit factor is intrinsically linked to continued participation in crowdsourcing. However, we excluded it to focus on behavioral aspects. The exclusion guarantees a focused examination of the factors influencing the intent to participate. Additionally, due to price value overlaps with the SETM element of cost, integrated into perceived concerns, it was also removed [23]. Furthermore, the study investigates the moderating roles of demographic variables (gender, age, occupation, income, and type of job) on the factors affecting couriers' behaviors to continue working in last-mile delivery.

By integrating SETM and UTAUT2, the purpose of this study is to provide a thorough comprehension of the features that impact the sustained participation of crowdsourcing couriers. This will enable crowdsourcing platforms to develop strategies to attract and retain couriers, ensuring the sustainability of crowdsourced delivery services. The study adopts a firmly quantitative approach. The proposed model is tested empirically through survey data, and then analyzed using Structural Equation Modeling (SEM). Although the model draws from the theoretical frameworks of SETM and UTAUT2, all variables are

clearly defined and measured quantitatively to assess the relationships that affect couriers' continued participation in crowdsourced last-mile delivery.

3.1.2 Hypotheses:

After conducting a comprehensive review of relevant literature, a set of hypotheses has been developed. In assessing each element within the framework of crowdsourced last-mile delivery, items have been adapted and developed for Couriers' Behavior as shown in [Table 3](#).

1. Esteem influence

While earnings are important to a crowdworker, a courier is more concerned with factors like acknowledgment, opportunities for career progression, and working conditions [93]. According to Blau [22], Ye and Kankanhalli [21], Geri et al. [78], and Sun et al. [54], people interact with one another in social exchanges that are motivated by a variety of Expectations regarding value, including credibility, social standing, and esteem. It indicates that a person's commitment to stay in their position might stem from their belief that it will improve their status. People can use their image as a resource for acquiring and keeping position in a group of individuals or society. Many people find purpose in their professions and lives, and they look for validation in a variety of ways: from social recognition among colleagues, which satisfies their need for appraisal, to organizational reputation among leadership, which recognizes accomplishments, and from consumer acknowledgment as seen in study by Liu et al. [14], Lin et al. [19], and Buldeo Rai et al.

[72]. Reputation influence is a significant external incentive that affects engagement in the web-based collaborative activities and community interactions [20, 55, 60, 69, 95]. Consequently, the following hypothesis is put forth:

H1. Esteem Influence positively impacts couriers' behavioral intention to stay involved in crowdsourced last-mile delivery.

2. Economic benefit

Income influences employees' choices to engage in and stay in a job. People in all professions tend to stay employed in a comfortable standard of living [16, 60, 69]. Couriers can utilize this feature to make money during their available time. Economic benefit (EB) is clearly important, even though reasons for working could differ [14, 21, 22, 54, 58, 78, 94, 95]. Monetary rewards are usually one of the incentives for couriers provided in crowdsourced delivery platforms, who expect to receive these rewards when their services are chosen [112]. Previous studies highlight the pivotal role of extrinsic motivators, such as economic benefits, in couriers' participation [12, 13, 15, 57]. Research by Terwiesch and Xu [113] provides an example of how financial incentives enhance the courier's involvement in crowdsourcing; additional evidence is deduced from platforms like TaskCN, where the chosen worker expected to be rewarded financially for each task completed [77]. According to the social exchange theory, the monetary incentive motivates individuals to participate [21, 58]. Consequently, companies must develop a suitable system for task distribution and reward to encourage employees to engage in the service [28, 72, 90]. Delivery companies should implement an incentive plan to incentivize

couriers to continue working with them [59, 96]. Consequently, the following hypothesis is put forth:

H2. Economic benefit positively influences couriers' behavioral intention to stay involved in crowdsourced last-mile delivery.

3. Effort expectancy

Effort expectation (EE), like ease of use in TAM theory, is concerned with how individuals, such as couriers, perceive the ease with which they can engage in crowdsourced logistics. The more couriers believe that the crowdsourced logistics models are understandable and straightforward, the more likely they are to employ it [19, 55, 69, 96]. The degree of understanding and compliance that couriers perceive crowdsourcing logistics model directly influences their willingness to participate [69]. For instance, if users believe the participation rules are clear, such as job instructions or delivery guidelines, they are more confident in completing tasks without unnecessary challenges. Perceived ease of use is critical for fostering continuing involvement in last-mile delivery [96]. For the logistics network to encourage ongoing participation, perceived ease of use is a pivotal factor [96]. Furthermore, studies indicated that user satisfaction in logistics operations is mostly determined by simplicity of use, which also increases behavioral intentions to maintain involvement [12, 15]. The more couriers believe that the crowdsourced logistics models are understandable and straightforward, the more likely they are to employ them [55, 69, 96]. In other words, the relationship between effort expectancy and continued behavioral

intention is critical for assuring ongoing courier participation in crowdsourcing logistics. Consequently, the following hypothesis is put forth:

H3. Effort expectancy positively influences couriers' behavioral intention to stay involved in crowdsourced last-mile delivery.

4. Hedonic motivation

The study's definition of hedonic motivation (HM) concerns the level to which an individual will enjoy the participation in crowdsourced last-mile delivery. Similarly, previous studies have suggested that emotional motivation has an important impact on the participation behavior of crowd couriers in urban crowdsourcing logistics [23, 59, 90]. Higher satisfaction increases the possibility that an individual will participate in crowdsourcing again. Participants' desire to engage in crowdsourcing is favorably influenced by enjoyment, according to research by Liang et al. [69], and Zhang [60]. Additionally, satisfaction increases individuals' habit to take part in crowdsourcing [79, 96]. When jobs are adaptable and match an individual's skills, crowdsourced workers can confidently approach them and enjoy the process [59, 96]. Although some studies have found that traditional jobs (e.g., full-time, part-time, and independent short-term contracts) may not provide the same level of flexibility and autonomy, the engagement in crowd logistics has been noted as unenjoyable in some cases, leading to stress and burnout when tasks exceed workers' abilities [69], other research has found that job enjoyment, depending on flexibility and autonomy, contributes positively to individual's behavioral intention in crowd logistics [21, 114]. Therefore, the following hypothesis is proposed:

Therefore, the following hypothesis is proposed:

H 4: Hedonic motivation positively influences couriers' behavioral intention to stay involved in crowdsourced last-mile delivery.

5. Work autonomy

According to Hackman and Oldham [115], work autonomy (WA) denotes an individual's level of liberty, self-reliance, and authority in choosing the activities and processes carried out at work. Previous studies have demonstrated the influence of job freedom of choice on workers' judgments of their overall performance [21, 22] and their willingness to begin, carry out, and finish task [16]. Huang et al. [59] found that people are considerably more motivated to continue in their positions as couriers in a favorable work environment. Furthermore, Alnaggar et al. [49] have shown that the schedules and conditions of crowdworkers affect their efficacy. When given the option to select several factors, such as delivery time, routes, and destinations, participants exhibit a higher inclination to remain in current positions [14, 92]. Consequently, the following hypothesis is put forth:

H 5: Work autonomy positively influences couriers' behavioral intention to stay involved in crowdsourced last-mile delivery.

6. Perceived concern

According to Jamal [116], job concern is a person's reaction to aspects of their workplace that endanger their mental and physical health. Moreover, Podsakoff et al. [117] and [54] characterized negative psychological and physical responses that happen when job responsibilities do not meet employees' capabilities, supplies, or demands. This can result in unhealthy conditions or severe disability. Couriers worry a lot about risk when it comes

to last-mile delivery since it might result in financial losses. Liu et al. [91], Wang et al. [118], and Huang and Ardiansyah [65] state that these concerns include unpredictability that could hinder the successful completion of allocated jobs. Money-related issues are listed, including cancelled tasks, misdirected deliveries, and problems with payments. Furthermore, concerns related to safety and health are considered [14, 20-22, 95, 97, 103]. Our study concentrates on perceived concern as the primary courier for continued participation in crowdsourced last-mile delivery. Although environmental and legal considerations are acknowledged as potential influencers, we have intentionally excluded them from our focus to maintain the specificity of our research [55, 72, 90, 96]. Consequently, the following hypothesis is put forth:

H6: Perceived concern negatively influences couriers' behavioral intention to stay involved in crowdsourced last-mile delivery.

3.1.3 Methodology of a Continued Couriers' Behavioral Intention Model

a. Survey Design

In this research, we will analyse the factors via survey. First, we discuss the survey design, then we will discuss the statistical techniques used to analyse the responses, using IBM SPSS, and IBM Amos 26.0.

Table 3 presents the selected items for each construct (factor), with three to four questions included for each in the survey. These items have been developed and modified based on the factors selected from the original UTAUT2 [23] and the SETM [21, 22], to suit the specific context of the study, see Section 3 for a detailed discussion. The survey uses a five-point Likert scale to answer the questions, with options from strongly disagree (1) to strongly agree (5). For this survey, the five-point scale is appropriate due to its ease of use and the consideration that the sample includes amateur couriers in last-mile delivery as explained in Section 3.1.3.b.

The translation process followed a multi-step approach to ensure linguistic and cultural validity. First, a bilingual expert translated the survey into Arabic, ensuring the meaning remained intact rather than a literal translation. A second bilingual expert conducted a back translation, converting the Arabic version back into English. A committee of logistics experts then reviewed both versions to ensure cultural appropriateness and identify inconsistencies or ambiguities. Finally, a pilot test was conducted on a sample of 33 participants. It led to minor adjustments based on their feedback to improve clarity and

comprehension, adding two questions (EI1 and PC4) and extra details to the information sheet. Cognitive interviews were also conducted with selected participants to confirm that questions were interpreted as intended across cultural contexts. An information sheet about the survey was designed to acquaint the participants with the topics and prevent inaccuracies in the responses. Consequently, the questionnaire items and the information sheet were modified based on the feedback. Ultimately, the survey was accessible in both paper and online formats through Google Forms, with the survey sample provided in [Appendix I](#).

b. Data collection and sampling

The research aims to survey diverse participants in terms of age, gender, and occupation, income and type of job to ensure that the data reflect the population of Saudi Arabia. Data were collected over six months, from October 2023 to March 2024. The survey was disseminated via companies' couriers list and online platforms including social media, while hard copies were distributed to students, company employees working in the field, and other groups of people who are working in delivery.

In our survey we employ a set of 22 items, therefore, a minimum of 110 ($22 \times 5 = 110$) participants is required. Note that all items should exhibit a factor loading, which defines as a correlation coefficient indicating the strength of the relationship between an observed variable and a latent factor, of at least 0.70. Furthermore, it is important to highlight that a participant-to-item ratio of 3:1 ($n = 22 \times 3 = 66$) would be considered insufficient, as outlined by Thompson [119] and Worthington and Whittaker [120].

Table 3 Items Used for Couriers' Behavior in Both Online and Paper Surveys

Category	Construct (Factor)	Items	Source adapted
Benefits	Esteem Influence (EI)	EI1 As a courier in crowdsourcing logistics, I earn trustworthiness.	[21, 22]
		EI2 As a courier in crowdsourcing logistics, I earn recognition.	
		EI3 As a courier in crowdsourcing logistics, I earn respect from others.	
		EI4 As a courier in crowdsourcing logistics, I earn a better image within the community.	
	Economic Benefit (EB)	EB1 Working as a courier benefits me financially.	[21, 22, 28, 94]
		EB2 My monthly income increases when I work in crowdsourcing logistics.	
		EB3 The primary reason to become a courier is to earn money.	
	Effort Expectancy (EE)	EE1 It is easy for me to work in crowdsourcing logistics skillfully.	[23]
		EE2 The rules and work methods in crowdsourcing logistics are clear and understandable.	
		EE3 Crowdsourcing logistics delivery is convenient. (such as easy to pick up and delivery, etc.).	
	Hedonic Motivation (HM)	HM1 Participating in crowdsourcing logistics is fun.	[23]
		HM2 Participating in crowdsourcing logistics is entertaining.	
	Work Autonomy (WA)	WA1 I have options to select my Participating schedule.	[21, 22, 49]
		WA2 I have options to select my delivery location.	
		WA3 I have options to select my delivery distance.	
Costs	Perceived Concern (PC)	PC1 I am concerned about payment delay or cancellation from customer.	[21, 58]
		PC2 I am concerned about the impact of Participation on my health.	
		PC3 I am concerned about the impact of participating on my security.	
		PC4 I am concerned that Restricted access in gated (compound) communities affects my participation.	
Outcome	Continued Participation Behavior Intention (BI)	BI1 I will continue to participate in crowdsourcing logistics in the future.	[23, 60]
		BI2 I will frequently Participate in the crowdsourcing logistics when available.	
		BI3 I am willing to recommend crowdsourcing logistics to my friends and family for participation.	

In addition to examining descriptive outcomes, SPSS Amos 26.0 tool is utilized to conduct the Structural Equation Modeling (SEM), the Confirmatory Factor Analysis (CFA), and

the path analysis [121]. SEM employs a combination of factor assessments with multi-variable regression; therefore, it allows for the simultaneous examination of all the relationships, including observed and unobserved variables. Moreover, it can account for measurement errors in the variables being studied Hair et al. [122]. Our study followed the recommended approach by James and David [123] conducting CFA to assess the reliability and the validity of the measured constructs and then evaluating the structural relationships using path analysis to test the suggested hypothesis in the structural framework.

3.2 Courier Acceptance Probability of Requests Model

In this section, we present a novel data-driven approach to model the probability of couriers' acceptance of a request. Employing survey data, our method incorporates important quantitative variables such as delivery distance, delivery time, compensation, and associated courier control variables into various machine learning models. Specifically, the objective is to develop an integrated model that characterizes the probability of request acceptance by such key constituents and further enhances our understanding of the driver-centric factors in delivery task acceptance.

3.2.1 Predictive Modeling Techniques

In our predictive framework, we apply **Logistic Regression (LR)** as the foundational model applicable for binary labels (outcomes) representing acceptance or rejection of a task. The model can, therefore, capture well the impacts of the control variables,

costs, distance, and maximum delivery times, where y is the binary outcome (dependent) variable with a value of 1 for acceptance and 0 for rejection, as implied in [Figure 2](#) [124], while the input attributes $x_1, x_2, \dots, x_n$ are the demographic (control) variables, cost, distance, and time, the logistic regression model is:

$$P(y = 1) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \dots + \beta_n x_n)}} \quad (1)$$

The acceptance probability is represented as $P(y = 1)$; the intercept term, which defines a constant coefficient, is represented as β_0 ; and the other coefficients associated with the independent variables are $(\beta_1, \dots, \beta_n)$, with the values of the independent variables being $(x_1, x_2, \dots, x_n)$. The expected probabilities form an interval $[0, 1]$ due to the logistic function. The coefficients $(\beta_0, \dots, \beta_n)$ in this equation are calculated during logistic regression training to determine which parameters accurately fit the data. This logistic function assures that these probabilities lie between 0 and 1, providing a clear and understandable framework for judging courier decisions. Using such a model, one can compare the accuracy yielded with a more complex one, serving as a benchmark.

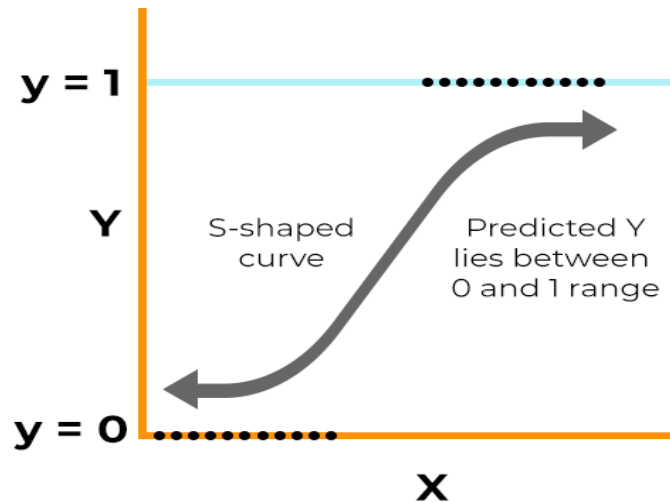


Figure 2 Logistic model

To further enhance the predictive accuracy and understand the complex relationship among the variables more comprehensively, we have then considered some advanced ML approaches:

Random Forest (RF): The great advantage of RF is its ensemble approach for generating several decision trees, as shown in [Figure 3](#), which makes the predictive result much more stable and accurate [125]. Such a method encompasses the difficulty presented by large, diverse sets of features in our dataset, from people to task-specific attributes such as distance, compensation, and time, and overcomes the overfitting problem of a single decision tree. Through outcome aggregation from several trees, Random Forest boosts up the accuracy of the results by performing 'bagging' or bootstrap aggregating, which ascertains that the model will perform well with several subsets of the dataset. This makes Random Forest quite powerful in discovering such complex interactions and dependencies that alter the acceptability of courier tasks, hence giving us better abilities to predict outcomes in varied and sometimes unpredictable environments. The following equation summarizes the Random Forest model used in this study:

$$\hat{y}_{acceptance} = \frac{1}{T} \sum_{t=1}^T f_t(x) \quad (2)$$

Where:

- $\hat{y}_{acceptance}$: Predicted task acceptance by the courier.
- T : Total number of decision trees.
- $f_t(x)$: Prediction from the t -th decision tree based on the input features (gender, type of job, compensation, distance, delivery time).

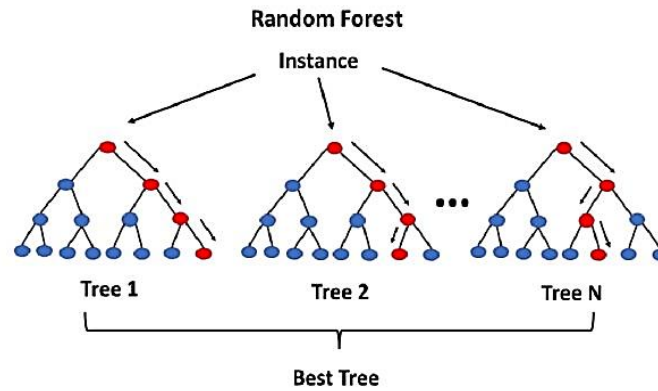


Figure 3 Random Forest model

Artificial Neural Networks (ANN): ANNs are also commonly known as neural networks and are based on biological human brain systems. ANN can achieve countless different tasks, such as regression and classification, which are brain functioning processes. A typical multilayer feed-forward network contains three basic elements, as illustrated in [Figure 4](#), an input layer, hidden layers, and an output layer [126]. The input layer handles a high degree of nonlinear input information, ensuring the model can process complex data effectively. Hidden layers between the input and output layers consist of varying numbers of neurons. Increasing the number of neurons in these layers enhances the network robustness and non-linearity, improving its capacity to model complex relationships. Lastly, the output Layer is responsible for dispatching and reviewing the processed information, balancing the connections between neurons to generate the final output.

ANN has been used in our current study to model the complex and non-linear relationships between various variables, including distance, cost, and delivery time, that play a very significant role in accepting courier tasks. Since ANN can perform deep learning, it can identify those hidden patterns in the data that are usually left unnoticed by more

straightforward models like Logistic Regression. These networks operate with many processing layers, learning the non-linear feature transformation and interaction among input features. This increases the model's capability to generalize and make fine predictions. ANN would provide a robust tool that can identify subtle determinants of the decision-making process in accepting courier tasks. The ANN model in this study can be expressed as follows:

$$\hat{y}_{acceptance} = f(W^n \cdot g(W^{n-1} \cdot g(W^1 \cdot x_i + b^1) + \dots + b^n) + b^{n-1}) \quad (3)$$

Where:

- $\hat{y}_{acceptance}$: Predicted courier task acceptance (output of the network)..
- $x_i = (x_1, \dots, x_n)$: Input vector consisting of features such as distance, compensation, delivery time, gender, and type of job.
- W^n : Weight matrix for the nth layer, representing the importance of inputs for that layer.
- b^n : Bias vector for the nth layer, allowing the model to shift the activation function.
- g : Activation function (e.g., ReLU or sigmoid) applied at each hidden layer to model non-linear relationships.
- f : Output layer activation function, such as sigmoid (for binary classification) or SoftMax (for multi-class classification).
- n : Total number of layers in the ANN.

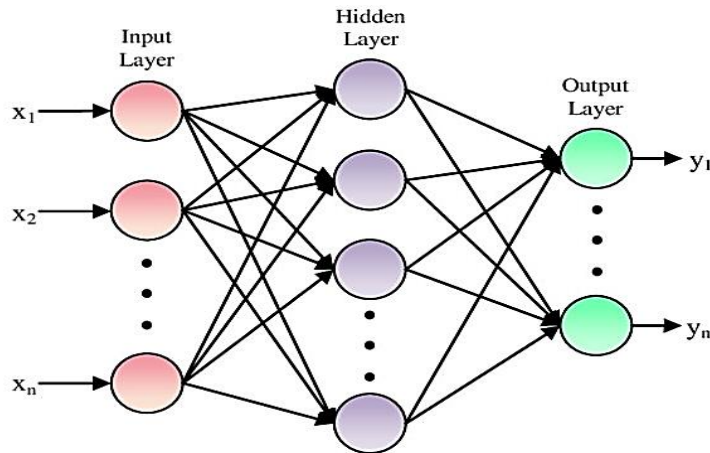


Figure 4 Artificial Neural Network model

Decision Tree (DT): DT consists of a root node, decision nodes, branches, and leaf nodes, see Figure 5 [127]. The root node represents the starting point, where the first condition is applied to split the input data. Decision nodes represent intermediate points in the tree where additional conditions (e.g., based on cost, distance, delivery time, gender, and type of job) are applied to further split the data. The branches indicate the possible outcomes of these conditions, leading to subsequent nodes. Lastly, the leaf nodes represent the terminal points of the tree, where the prediction outcome is determined, in our case, task acceptance by the courier ($v_1 = accept$) or ($v_2 = reject$). Although simpler than some models, DT allows us to rapidly identify and validate key predictive variables, which might increase the accuracy of simpler models. Furthermore, DT allows tracing made decisions step-by-step, providing an interpretable breakdown of how specific factors, such as delivery timing, distance, or demographic variables, either increase or decrease the probability of task acceptance. This interpretability makes DT especially valuable in understanding the importance of each input variable, allowing us to refine the model for the sake of transparency and aiding both model accuracy and practical application. The decision tree (DT) model for task acceptance in our study is as follows:

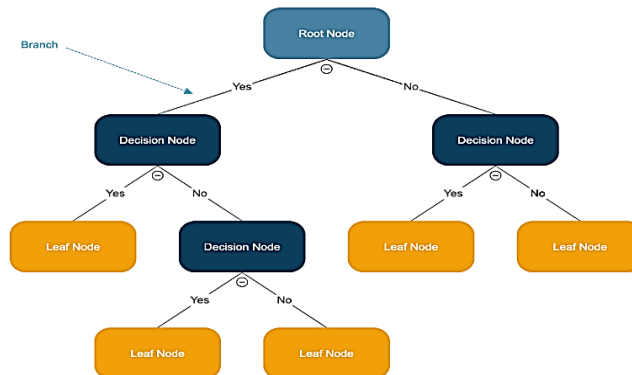


Figure 5 Decision Tree model

$$y_{acceptance} = \begin{cases} v_1, \text{if condition 1 is true} \\ v_2, \text{if condition 2 is true} \\ v_3, \text{if condition 3 is true} \\ \vdots \\ v_k, \text{if condition } k \text{ is true} \end{cases}$$

where $y_{acceptance}$ represents the predicted courier task acceptance outcome (e.g., Accept = 1, Reject = 0), v_1, v_2, v_3 denote Predicted outcomes (e.g., Accept or Reject) based on the conditions on input features such as cost, distance, delivery time, gender, and type of job. Each condition represents a decision node in the tree, and the outcome depends on the path followed through the tree.

Long Short-Term Memory (LSTM): LSTMs, a special case of ANNs, can handle sequential data relationships like in time series. In our study, the LSTMs are applied to follow up and predict changes occurring in courier task acceptance over sequences of deliveries [128]. Specifically, LSTM is good at picking out how the decisions of couriers may have changed due to their previous decisions based on their preferences in terms of cost, distance, and delivery time. By doing that, LSTM can tell if a courier that previously accepted tasks with very long delivery times and very high compensation has been more likely to accept future similar tasks. This is how such dependencies are captured through LSTMs to understand and predict the multifaceted behavior patterns of courier task acceptance, an added advantage for an improved predictive model. The LSTM memory cell, as illustrated in [Figure 6](#), has three critical components: the Forget Gate, Input Gate, and Output Gate, which control information flow via the cell state and hidden state,

allowing the model to capture long-term dependencies [129]. The Core LSTM Equation for prediction task acceptance is:

$$\hat{y}_{Acceptance} = f(W_o \cdot h_i + b_o) \quad (4)$$

Where:

- $\hat{y}_{Acceptance}$: Predicted courier task acceptance at time t (e.g., Accept=1, Reject=0).
- h_i : Hidden state for the i th layer.
- W_o : Output weight matrix, mapping the hidden state to the output.
- b_o : Output bias term.
- f : Activation function (e.g., sigmoid for binary classification).

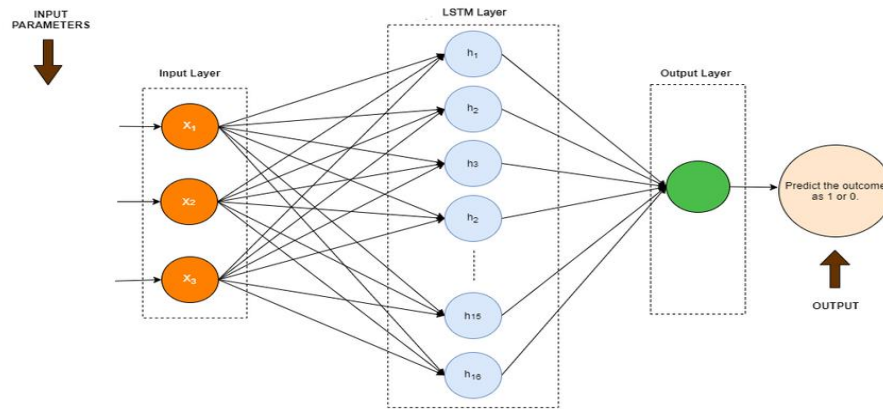


Figure 6 Long Short-Term Memory Model

Support Vector Machine (SVM): SVM classifies complex and high-dimensional data. With its multi-class support, SVM finds the most suitable hyperplane that will help in predicting the outcome of the assigned tasks based on the margins of decision boundaries shaped by the courier's demographic and task-specific variables [130] (see Figure 7). In our study, SVM is used to classify whether a courier task will be accepted or rejected, based

on task-specific and demographic features such as compensation, distance, delivery time, gender, and type of job. The decision function for the classification task is represented as:

$$f(x) = \text{sign}(w^t x + b) \quad (5)$$

Where:

- $f(x)$: The predicted class label (+1: Task Accepted, -1: Task Rejected).
- w^t : Transpose of the weight vector that determines the orientation of the separating hyperplane (H).

x : Input vector consisting of task-specific and demographic features (e.g., distance, compensation, delivery time, gender, and type of job).

b : Bias term, determining the position of the hyperplane.

$\text{sign}(\cdot)$: A function that returns the sign of the argument, indicating on which side of the hyperplane a given data point lies.

To find the optimal hyperplane that maximizes the margin between the two classes, the SVM solves the following optimization problem:

$$\min_{w,b} \frac{1}{2} \|w\|^2 \quad (6)$$

Subject to the constraints:

$$y_i (w^t x_i + b) \geq 1, \forall_i \quad (7)$$

Where:

- y_i : True class label for the i-th data point ($y_i = +1$ for Accepted, $y_i = -1$ for Rejected).
- x_i : Input vector for the i-th data point.
- $\|w\|^2$: The squared norm of the weight vector, which is minimized to maximize the margin.

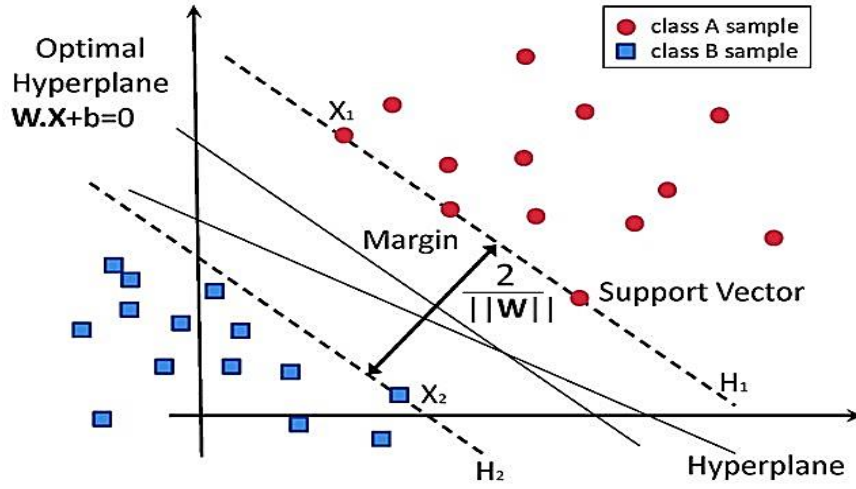


Figure 7 Support Vector Machine model

For nonlinear data, SVM employs a kernel function $K(x_i, x)$ to map the input data into a higher-dimensional space where a linear separation is possible [131]. The decision function then becomes:

$$f(x) = \left(\text{sign} \left(\sum_{i=1}^N \alpha_i y_i K(x_i, x) + b \right) \right) \quad (8)$$

Where:

- $K(x_i, x)$: Kernel function (e.g., Radial Basis Function (RBF)) that maps the inputs to a higher-dimensional space.
- α_i : Lagrange multipliers obtained from solving the dual optimization problem.

Extreme Gradient Boosting (XGBoost): XGBoost constructs a sequence of weak models, for example, decision trees, where each tree in the sequence aims to minimize the loss (error) of the one before it (see Figure 8) [132]. Hence, XGBoost takes these models and builds a more accurate model (learner). Therefore, XGBoost can become the best if used in places that require high accuracy and robustness.

Key equations in XGBoost are as follows:

1. Prediction Function: The prediction for the i -th data point is the sum of the predictions from all K decision trees:

$$\hat{y}_i = \sum_{k=1}^K f_k(x_i) \quad (9)$$

Here, $\hat{y}_i$ is the aggregated prediction for the i th data point, where $f_k(x_i)$ denotes the prediction made by the k th decision tree for the same data point.

2. Loss Function: The overall loss function $L(\phi)$ is a combination of a differentiable loss function and a regularization term for all K trees:

$$L(\phi) = \sum_{i=1}^n l(y_i, \hat{y}_i) + \sum_{k=1}^K \Omega(f_k) \quad (10)$$

- $l(y_i, \hat{y}_i)$ is the loss function that measures the prediction error for data point $i = 1, \dots, M$.
- $\Omega(f_k)$ is the regularization term that controls the complexity of the model, typically involving parameters that penalize the model for having too many.

3. Optimal Weights: The optimal weights in the model are calculated by balancing the first and second derivatives of the loss function, adjusted by the regularization parameter λ :

$$w_j^* = -\frac{G_j}{H_j + \lambda} \quad (11)$$

Here:

- G_j is the sum of the first derivatives of the loss function with respect to the predictions at the j -th node.
- H_j is the sum of the second derivatives of the loss function with respect to the predictions at the j -th node.
- λ is the regularization term that adds stability and prevents overfitting by penalizing the magnitude of the weights.

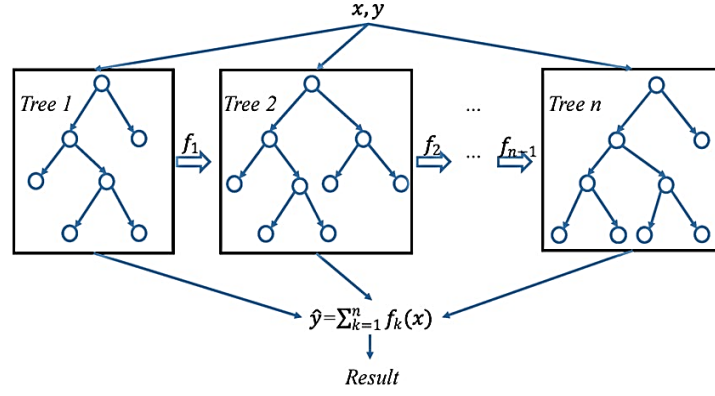


Figure 8 Extreme Gradient Boosting model

Gated Recurrent Unit (GRU): GRU, a form of recurrent neural network (RNNs), is optimized for sequential data, making it especially effective for understanding task variables. GRUs manage the flow of information using update and reset gates, which control memory retention, and forgetting of irrelevant information. This architecture gives GRUs the capability of effectively capturing both short-term and long-term dependencies, which may make them an ideal choice for modeling sequential behaviors in task acceptance based on factors like past decisions, delivery timing, and task attributes. The efficiency of GRUs in handling complex temporal patterns makes it very important in the prediction of courier task acceptance over time [133]. The equations below illustrate the GRU mechanism:

Update Gate:

$$z_t = \sigma(W_z x_t + U_z h_{t-1} + b_z) \quad (12)$$

- z_t : Update gate.

- σ : Sigmoid activation function.
- W_z : Weight matrix for the input x_t (task variables).
- U_z : Weight matrix for the hidden state h_{t-1} .
- b_z : Bias term.

Reset Gate:

$$r_t = \sigma(W_r x_t + U_r h_{t-1} + b_r) \quad (13)$$

- r_t : Reset gate which determines the influence of prior states on the current computation.
- W_r : Weight matrix for the input x_t .
- U_r : Weight matrix for the hidden state h_{t-1} .
- b_r : Bias term.

Candidate Hidden State:

$$\tilde{h}_t = \tanh(W_h x_t + U_h (r_t \odot h_{t-1}) + b_h) \quad (14)$$

- $\tilde{h}_t$: Candidate hidden state.
- $\tanh$: Hyperbolic tangent activation function.
- r_t : Reset gate.
- $\odot$: Element-wise multiplication.

Final Hidden State:

$$h_t = z_t \odot h_{t-1} + (1 - z_t) \odot \tilde{h}_t \quad (15)$$

- h_t : Final hidden state at time t.
- z_t : Update gate.

These equations explain GRUs' ability to handle sequential data effectively. The application of GRUs in our study improves the prediction of courier task acceptance by

effectively modeling the effects of past task acceptance patterns and other temporal variables. Figure 9 shows the basic architecture of GRU [134].

AlexNet: AlexNet is a variant of CNN, which is specifically designed to handle large-scale, high-dimensional data and thus allows the effective extraction of the intricate patterns within structured data, such as image data [135, 136]. In our study, AlexNet is applied to recognize task-specific attributes and behavioral trends that might make a difference in accepting courier tasks. By utilizing convolutional layers for spatially organized data, AlexNet can detect multiple layers of features, uncovering hidden relationships between factors like delivery distance, timing, and demographic details. Its deep-layered structure is especially suited for tasks that demand nuanced pattern recognition, enhancing the predictive reliability of task acceptance models. With its capacity to manage complex, high-volume data smoothly, AlexNet aids real-time decision-making, serving as a robust resource for dynamic, large-scale modeling of courier behavior. The AlexNet equation is:

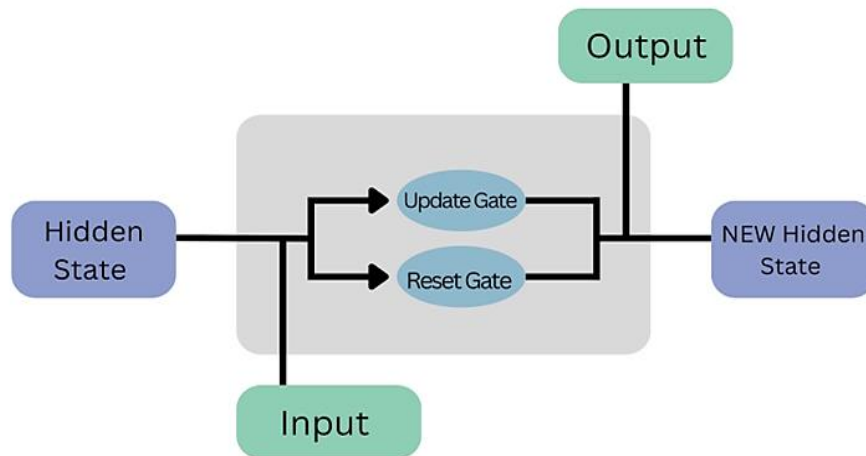


Figure 9 Gated Recurrent Unit model

$$y = (i, j, k) = \sum_{m=1}^M \sum_{n=1}^N w_k(m, n) \cdot x(i + m, j + n) + b_k \quad (16)$$

Where:

- $y(i, j, k)$: The output at position (i, j) in the k-th feature map, detecting task-specific patterns like courier preferences or decision trends.
- $x(i + m, j + n)$: Input data, representing structured details such as delivery distance, timing, and demographics.
- $w_k(m, n)$: The filter (kernel) for the k-th feature map, identifying key attributes influencing task acceptance.
- b_k : Bias term for the k-th feature map, adjusting the output.
- M, N : Size of filter dimensions, enabling pattern detection across the dataset.

Soft Voting: In this study, Soft Voting is employed as a robust ensemble technique that integrates the forecasts of several models via probability-based voting (see [Figure 10](#)). Rather than having each model deliver a singular, conclusive decision, Soft Voting allows each model to provide a probability for each potential outcome, including the likelihood of task acceptance or rejection. Probabilities are then averaged for each possible outcome to determine which has the highest overall probability [137], often correlated with variables such as delivery distance, timing, and demographic factors. In this case, the strengths and confidence levels of each model can be combined to improve the accuracy of the predictions by using a more advanced, probability-weighted consensus that correctly captures the complex patterns in the courier behavior. The following equation for this model is :

$$P(y = c) = \sum_{i=1}^N w_i \cdot P_i(y = c) \quad (17)$$

Simplified:

$$P(y = c) = \frac{1}{5} \sum_{i=1}^5 P_i(y = c) \quad (18)$$

Where:

- N : Total number of models in the ensemble. In this study, we consider LR, RF, DT, SVM, XGBoost so $N = 5$.
- $P(y = c)$: Final probability of class c (e.g., task acceptance or rejection).
- w_i : Weight assigned to the i -th model, reflecting its importance (equal weights are assumed here, $w_i = \frac{1}{N}$) because, in soft voting, each model's prediction is averaged without prioritizing any particular model's output.
- $P_i(y = c)$: Probability predicted by the i -th model for class c .

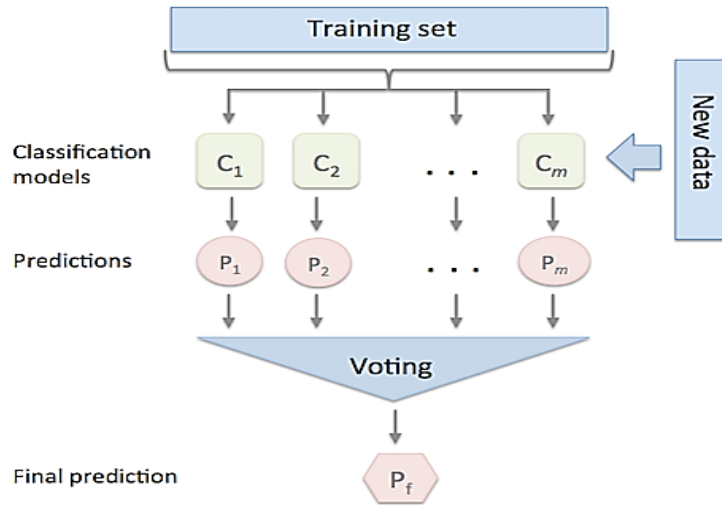


Figure 10 Soft Voting model

In conclusion, predictive techniques have significantly improved our ability to predict the acceptance of the courier's task accurately. There is, therefore, sufficiency in using multiple methods in the model, coupled with enhanced robustness in forecasting. These improvements then supported our efforts to adaptively fine-tune the operational strategies toward obtaining additional efficiency improvements while bringing about increased satisfaction for our courier base. As we apply these models, they provide a dynamic foundation for adapting to evolving market demands and optimizing future courier task management.

3.2.2 Methodology of Acceptance Probability Model

It is essential to consider demographic and quantitative attributes to predict the probability of acceptance of delivery tasks by a courier. Our investigation focuses on significant factors drawn from demographic (control) variables, such as gender, age, income, occupation, and type of job, as well as quantitative (stated preference) attributes like compensation, distance, and delivery time. Some of these variables, such as gender, type of job, compensation, distance, and delivery time, are identified as significant factors and are discussed in more detail in the results section. These five variables serve as inputs to model the acceptance of tasks, with the output being either acceptance or rejection, depending on six surveyed scenarios (refer to [Table 4](#)).

Table 4 Task Acceptance Scenarios

S1. For (20 SAR with 15km) What is the maximum time you are willing to deliver?	S2. For (20 SAR with 25km) What is the maximum time you are willing to deliver?	S3. For (30 SAR with 15km) What is the maximum time you are willing to deliver?	S4. For (30 SAR with 25km) What is the maximum time you are willing to deliver?	S5. For (40 SAR with 15km) What is the maximum time you are willing to deliver?	S6. For (40 SAR with 25km) What is the maximum time you are willing to deliver?
a. 20 min ☐	a. 20 min ☐	a. 20 min ☐	a. 20 min ☐	a. 20 min ☐	a. 20 min ☐
b. 40 min ☐	b. 40 min ☐	b. 40 min ☐	b. 40 min ☐	b. 40 min ☐	b. 40 min ☐
c. 60 min ☐	c. 60 min ☐	c. 60 min ☐	c. 60 min ☐	c. 60 min ☐	c. 60 min ☐
d. unwilling ☐	d. unwilling ☐	d. unwilling ☐	d. unwilling ☐	d. unwilling ☐	d. unwilling ☐

To further elucidate the application of our model, we examine a subset of the data. From the 345 total courier samples, we detail below the responses from the first two couriers across various scenarios (see Table 5).

Our data set's structure involves multiple columns representing different scenarios each courier might face. Specifically, the second and third columns of Table 5 capture

demographic variables: gender and type of job. Subsequent columns from four through nine represent various combinations of cost and distance:

- The fourth and fifth columns represent tasks with a cost of 20 SAR, covering distances of 15 km and 25 km, respectively.
- The sixth and seventh columns show tasks with a cost of 30 SAR, covering distances of 15 km and 25 km, respectively.
- The eighth and ninth columns show tasks with a cost of 40 SAR, covering distances of 15 km and 25 km, respectively.

Table 5 Example of Courier Response Data: gender, type of job, and Stated Delivery Preferences (compensation, distance, time)

Courier	Gender	Type of job	20 SAR- 15 km	20 SAR -25 km	30 SAR - 15 km	30 SAR - 25 km	40 SAR - 15 km	40 SAR - 25 km
1	Male	Committed	60 minutes	unwilling	40 minutes	60 minutes	40 minutes	40 minutes
2	Female	Occasional	20 minutes	unwilling	40 minutes	40 minutes	40 minutes	40 minutes

Each scenario offers couriers four potential time slots for task completion: unwilling, 20 minutes, 40 minutes, and 60 minutes. Couriers select one of these options based on their willingness and capability to meet the maximum delivery time.

From the dataset, we note:

- The compensation variables are set at three distinct values: 20, 30, and 40 SAR.
- The distance variables are set at two measures: 15 and 25 kilometres.

- Time options available for selection has four options: unwilling, 20, 40, and 60 minutes.

For instance, consider the responses in the fourth column of Table 5:

- A courier faced with a 20 SAR, 15 km task might accept a maximum delivery time of 60 minutes, implying acceptance at shorter times (20 and 40 minutes) as well, which would reflect in our model with an output value of 1 (accept).
- Conversely, should the courier express unwillingness for a 20 SAR, 25 km task, as seen in the fifth column, it indicates a rejection of all time slots, thereby assigning an output value of 0 (reject) across the 20, 40, and 60-minute marks.
- If a 30 SAR, 15 km task is accepted with a maximum of 40 minutes, as in the sixth column, it suggests acceptance at 20 and 40 minutes but not at 60 minutes.

Similarly, another courier might select a 20-minute maximum time for a 20 SAR, 15 km task, indicating an acceptance at the shortest available time frame and rejection of the longer time frames (40 and 60 minutes), which would again reflect in the output values accordingly. Such patterns repeat across the dataset and help comprehensively understand courier preferences and limitations.

These observed choices and patterns lead to new rows in our dataset, capturing the nuanced acceptance levels across various scenarios and enhancing our model's predictive accuracy.

As seen in Table 6, the extended data matrix provides a detailed view of these dynamics.

In our study, we utilize a dataset composed of 345 questionnaires, capturing both demographic attributes and stated preferences related to delivery tasks. The main variables include gender, income, age, type of job, compensation, distance, and delivery time. The variables are converted into numerical form to facilitate predictive modeling:

- Gender (categorical input): male =1, female =2

- Type of job (categorical input): occasional=1, committed=2, none =3
- Compensation (ordinal input): 20, 30, and 40 SAR
- Distance (ordinal input): 15 km and 25 km
- Delivery Time (ordinal input): 20, 40, and 60 minutes
- The output variable (label is categorical) indicates whether a delivery task is accepted or not is encoded as follows: Accept =1 and Reject =0.

Table 6 Detailed scenario-based analysis of courier task acceptance

Scenarios	Couriers	Independent variables					Dependent variable
		Gender	Type of job	compensation (SAR)	Distance (km)	Time (min)	Output (accept)
S1	1	Male	Committed	20	15	20	1
				20	15	40	1
				20	15	60	1
S2				20	25	20	0
				20	25	40	0
				20	25	60	0
S3				30	15	20	1
				30	15	40	1
				30	15	60	0
S4				30	25	20	1
				30	25	40	1
				30	25	60	1
S5				40	15	20	1
				40	15	40	1
				40	15	60	0
S6				40	25	20	1
				40	25	40	1
				40	25	60	0
S1	2	Female	Occasional	20	15	20	1
				20	15	40	0
				20	15	60	0
S2				20	25	20	0
				20	25	40	0
				20	25	60	0
S3				30	15	20	1
				30	15	40	1
				30	15	60	0
S4				30	25	20	1
				30	25	40	1
				30	25	60	0
S5				40	15	20	1
				40	15	40	1
				40	15	60	0
S6				40	25	20	1
				40	25	40	1
				40	25	60	0

Our predictive model is designed to assess the likelihood of task acceptance based on the former variables, offering insights into the decision-making patterns of couriers. [Figure 11](#) illustrates the methodology used. It starts with data collection, where raw data is acquired from various sources. In our case, we use online and paper-based survey.

The details of steps are as follows:

Data preprocessing: including feature selection to identify the significant factors, feature transformation (scaling the ordinal features using MinMax scaler), and label encoding the categorical features.

Data Splitting: we split the data into training and testing models. using an 80% training and 20% testing split.

Model Planning: our problem falls under supervised learning problem in machine learning. Namely, it is a binary classification problem. We selected standard and advanced machine learning techniques known for their accurate predictive capability. These include LR, DT, RF, XGBoost, SVM, ANN, LSTM, GRU, AlexNEt, and Soft Voting.

Model Execution: we tested various machine learning techniques such as LR, DT, RF, XGBoost, SVM, ANN, LSTM, GRU, AlexNEt, and SoftVoting to capture the intricate patterns within the dataset. These methodologies are applied to the 6210 data samples (18×345) data samples, as each courier generates 18 new options, as described in [Table 6](#).

This section further outlines the selection and configuration of ML models employed in this study for predicting the couriers' acceptance of delivery tasks. The proposed models were chosen based on their effectiveness in handling classification tasks while balancing

complexity, interpretability, and performance. Each represents different potential decisions by the couriers based on the structured scenarios provided. By comparing the actual data outcomes with the predicted values from proposed models, we can identify the most effective techniques for forecasting courier behavior in delivery settings. The models and parameters presented in Table 7 were identified using Grid Search Stratified k-Fold cross-validation (CV). We tested and implemented classic ML models, such as LR, DT, RF, XGBoost, and SVM, and advanced deep learning architectures like ANN, LSTM, GRU, and ALexNet. A Meta Ensemble (Soft Voting) was further applied to the combination of LR, RF, DT, SVM, and XGBoost to improve the robustness and accuracy. Deep learning models were elaborated carefully with a specific configuration, while classic models were derived based on simplicity and effectiveness. Hyperparameters were used in the optimization of all models concerning accuracy, recall, precision, and F1-score to ensure comprehensive performance. To assess the performance of the predictive models, we used the following evaluation metrics:

Accuracy:

Measures the proportion of correctly predicted instances (both positive and negative) out of the total instances.

$$\text{Accuracy} = \frac{(TP + TN)}{(TP + TN + FP + FN)} \quad (19)$$

Precision:

Indicates the proportion of correctly predicted positive instances out of all predicted positive instances.

$$\text{Precision} = \frac{(TP)}{(TP + FP)} \quad (20)$$

Recall:

Reflects the proportion of actual positive instances that were correctly predicted.

$$\text{Recall} = \frac{(\text{TP})}{(\text{TP} + \text{FN})} \quad (21)$$

F1-Score:

The harmonic mean of precision and recall, providing a balanced metric for imbalanced datasets.

$$\text{F1-Score} = 2 \times \frac{(\text{Precision} \times \text{Recall})}{(\text{Precision} + \text{Recall})} \quad (22)$$

Where:

- TP (True Positives): Correctly predicted positive instances.
- TN (True Negatives): Correctly predicted negative instances.
- FP (False Positives): Incorrectly predicted positive instances.
- FN (False Negatives): Incorrectly predicted negative instances.

More details on the evaluation outcomes are provided in the section 4. Result.

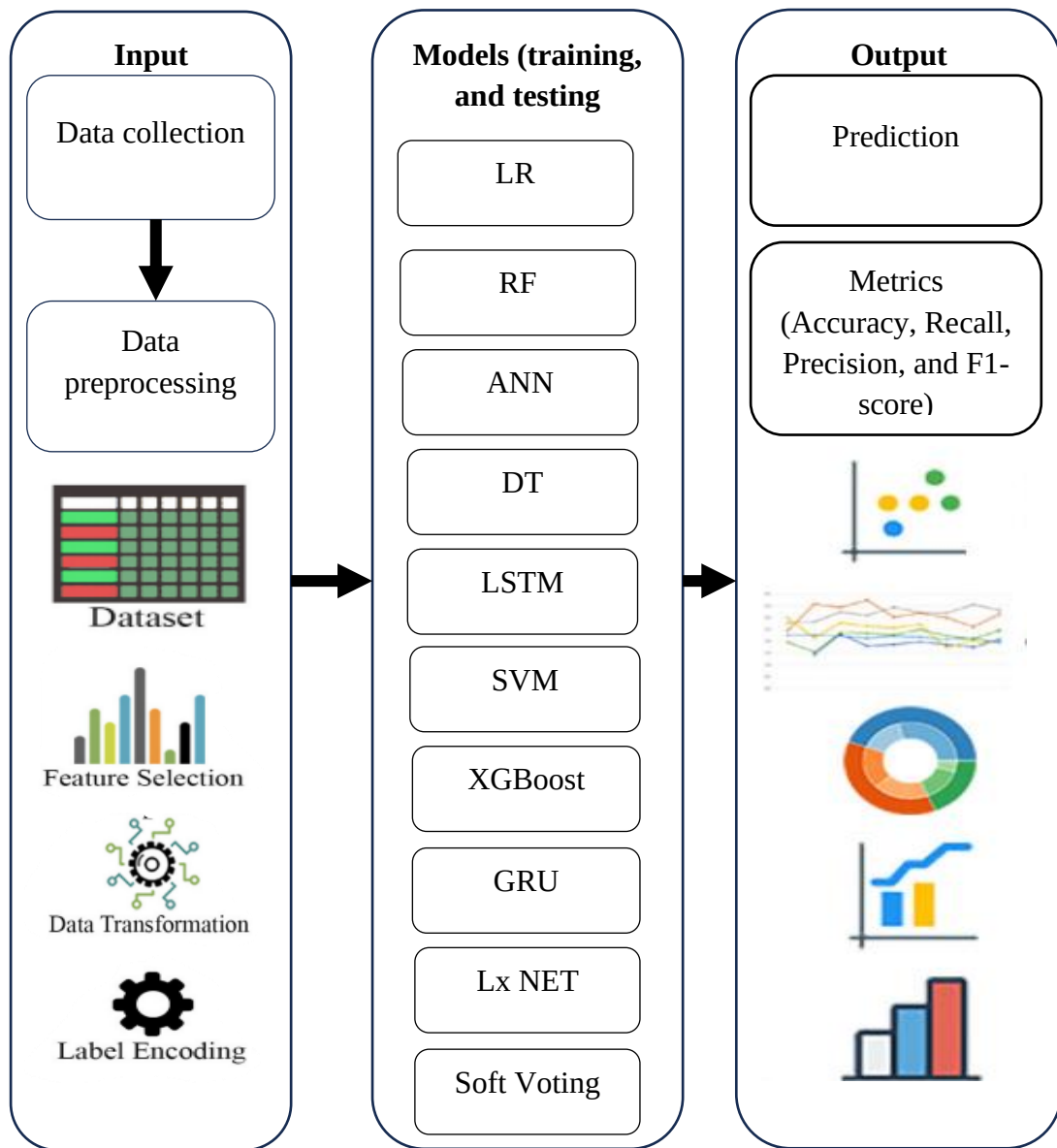


Figure 11 Proposed Acceptance Probability Model

Table 7 Description of Proposed Models Architecture for Acceptance Probability

Model	Key Parameters
Logistic Regression (LR)	regularization parameter(C)=10.0, max_iter=200, solver='lbfgs', random_state=40
Random Forest (RF)	n_estimators=200, max_depth=50, min_samples_split=2, random_state=40
Artificial Neural Network (ANN)	Input: Dense(64, relu), hidden: Dense(64, relu), output: Dense(1, sigmoid), optimizer=Adam, loss function= binary_crossentropy, epochs=50, batch size=32, verbose=1
Decision Tree (DT)	max_depth=50, min_samples_split=2, random_state=40
LSTM	Input: LSTM(50), output: Dense(1, sigmoid), optimizer=Adam, loss function= binary_crossentropy, epochs=50, batch size=32, verbose=1
Support Vector Machine (SVM)	regularization parameter(C) =1.0, kernel='rbf', gamma='scale', random_state=40
XGBoost	n_estimators=200, learning_rate=0.1, max_depth=30, eval_metric='logloss', random_state=40
GRU	Input: GRU(50), output: Dense(1, sigmoid), optimizer=Adam, loss function= binary_crossentropy, epochs=50, batch size=32, verbose=1
AlexNet	Input: Dense(64, relu), output: Dense(1, sigmoid), optimizer=Adam, loss function= binary_crossentropy, epochs=50, batch size=32, verbose=1
Meta Ensemble (Soft Voting)	Combination of LR, RF, DT, SVM, XGBoost (Soft Voting)

CHAPTER 4

DATA ANALYSIS AND RESULTS OF CONTINUED COURIERS' BEHAVIORAL INTENTION MODEL

4.1 Data Analysis and Results of Continued Couriers' Behavioral Intention Model

4.1.1 Descriptive Results

A total of 411 individuals (couriers) participated in the survey, with 377 contributing online and 34 submitting their responses on paper. Data was collected from couriers in crowdsourced last mile delivery in Saudi Arabia from October 2023 to March 2024. The collected data was initially pre-processed and filtered using Pandas' library in Python. During this stage, the data was to remove questionnaire samples that lacked relevance to our study due to uniform responses across all survey questions. The aim was to clean and regulate the irrelevant samples. After discarding irrelevant data, which did not influence the study's quality due to repetitive responses, 66 questionnaires were removed, and the remaining 345 were analyzed.

Table 8, and Figure 12 shows the demographic breakdown of participants. A majority, 74%, were male, while 26% were female. The age group with the highest representation was 18–25 years, making up 54% of all participants. Following closely were those aged 26–35 years, comprising 32% of the participants. Regarding occupation, most were students (55%), with a smaller portion being employed (19%), and the rest including job seekers, retirees, or other statuses making up 18%. Self-employed individuals represented

the smallest group at 8%. In terms of income, most participants earned less than 2000 SAR (52.5%), followed by 2000-5000 SAR (32.5%), with a minority earning more than 5000 SAR (15%). Participants were also asked about their preferred delivery task type, whether occasional (available for uncertain periods with pay per order), committed (available for a fixed period with pay per order and hourly pay), or no preference. Of all the respondents, 44% (n=151) preferred occasional tasks, 41% (n=141) preferred committed tasks, and 15% (n=53) had no preference. Moreover, [Figure 13](#) and [Figure 14](#), respectively imply the demographic distribution across the different ages, income, occupation, and type of job of male and female. For male, the majority are in the age group of 18-25, students with an income of more than 5000 SAR , and involved in committed jobs, while for female, the majority belongs to age group of 18-25, students with an income of less than 2000 SAR and involved in occasional jobs.

Table 8 Demographic Results.

Demographic Characteristics		Frequency(n)	Percentage (%)
Gender	Male	255	74
	Female	90	26
	Total	345	100
Age	18-25 years	187	54
	26-35 years	110	32
	>35 years	48	14
Occupation	Student	190	55
	Employed	65	19
	Self-employed	29	8
	Other	61	18
Income	Less than 2000 SAR	181	52.5
	2000-5000 SAR	112	32.5
	More than 5000 SAR	52	15
Type of Job	Occasional	151	44
	Committed	141	41
	None	53	15

4.1.2 Measurement Model Assessment

According to James and David [123], a proper statistical analysis should begin by evaluating the measurement framework before moving on to the structural framework. This involves using CFA to assess the internal consistency, composite reliability, and convergent with discriminant validity of the 7 factors or variables. The completed measurement model can be found in [Appendix II](#).

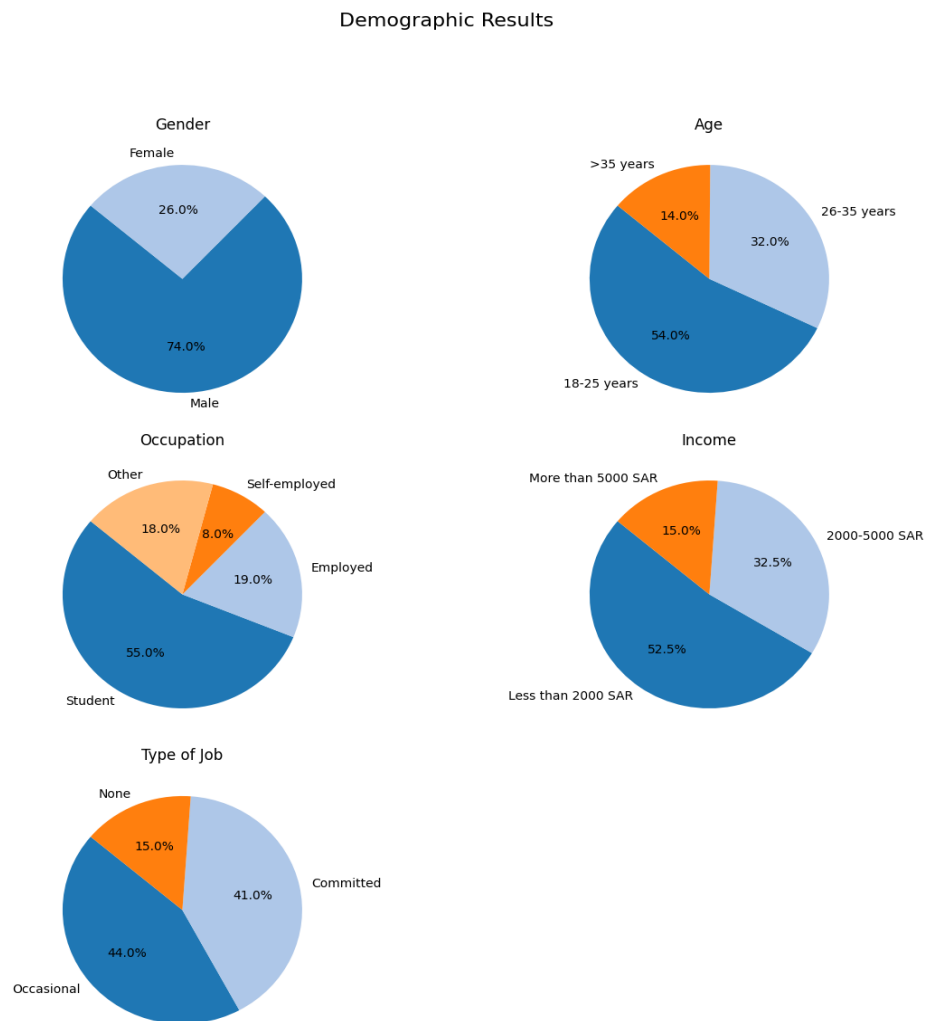


Figure 12 Demographic results

Male Gender Distribution Across Demographics (Age, Income, Occupation, Type of Job)

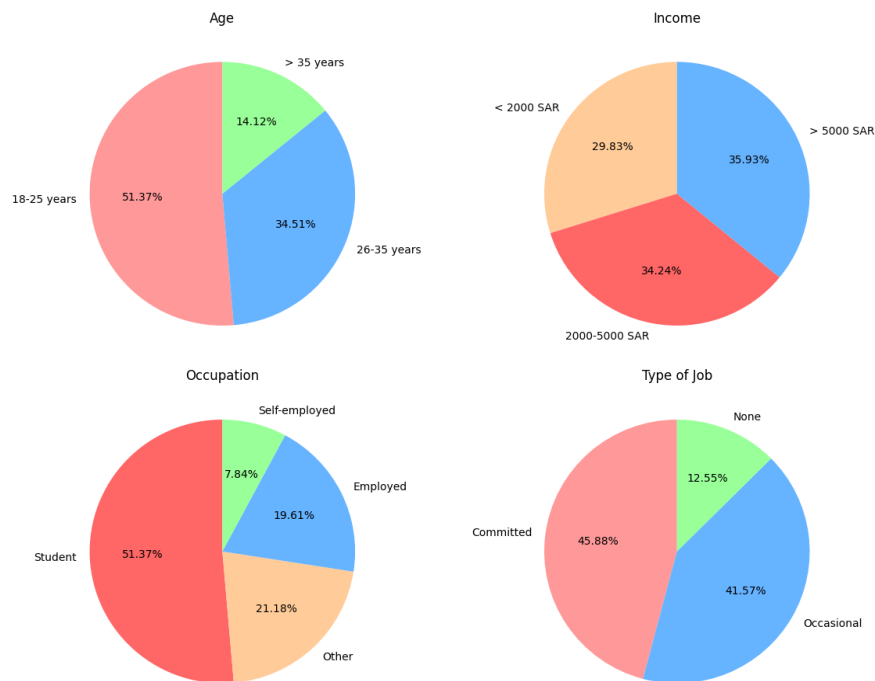


Figure 13 Male demographic results

Female Gender Distribution Across Demographics (Age, Income, Occupation, Type of Job)

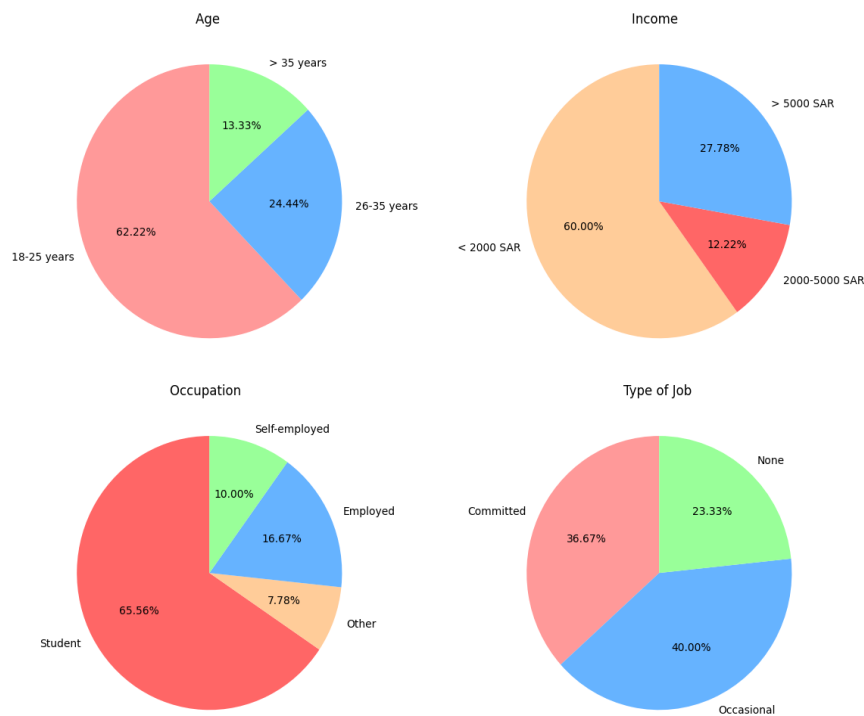


Figure 14 Female demographic results

[Table 9](#) presents the results of the assessment of internal consistency using factor loading, Cronbach's alpha, and Composite Reliability (CR). Factor loading indicates the correlation between an item and its respective construct and is used as a measure of commonality. To meet the convergent validity criterion, each factor loading should ideally be above 0.70 [122]. Cronbach's alpha measures the correlation of responses of a construct's items and has a well-established threshold of 0.70 [138]. Similarly, CR is another indicator of internal reliability, and a threshold of 0.70 or higher is recommended to ensure each item represents the same construct [122]. Cronbach's alpha is calculated using SPSS, while CR and Average Variance Extracted (AVE) with values between 0 and 1 are calculated following the formulas provided in Hair et al. [122] to evaluate the internal consistency of the items. Convergence validity is confirmed when AVE greater than 0.5 [139]. In addition to these reliability measures, the mean and Standard Deviation (SD) of each item were computed to analyze the central tendency and distribution of the data (see [Appendix IV](#)). Overall, all constructs in this study exhibit strong reliability, as indicated by the factor loadings, Cronbach's alpha, and CR values are above 0.70, AVE values greater than 0.5.

Furthermore, The study investigated the discriminant validity of the seven components to ensure that each is distinct [122]. Standard criteria were utilized to analyse the discriminant validity [139]. We use Amos 26.0 to determine the Maximum Shared Variance (MSV) and Average Shared Variance (ASV). These metrics play a crucial role in measuring discriminant validity. Discriminant validity is met when MSV is less than AVE, and ASV is less than MSV[140]. As shown from the results in [Table 10](#), the conditions are satisfied, yielding that the constructs are distinct.

Table 9 Internal reliability and convergent validity

Construct	Item	Factor Loading	Cronbach's alpha	CR	AVE	Mean	SD
Esteem Influence	EI1	0.84	0.91	0.91	0.72	3.33	1.32
	EI2	0.86				3.23	1.26
	EI3	0.90				3.36	1.26
	EI4	0.78				3.21	1.29
Economic Benefit	EB1	0.90	0.89	0.89	0.73	3.54	1.21
	EB2	0.85				3.59	1.14
	EB3	0.81				3.67	1.26
Effort Expectancy	EE1	0.82	0.87	0.88	0.70	3.37	1.32
	EE2	0.83				3.30	1.30
	EE3	0.86				3.38	1.27
Hedonic Motivation	HM1	0.91	0.89	0.90	0.81	3.10	1.25
	HM2	0.89				3.03	1.24
Work Autonomy	WA1	0.76	0.85	0.85	0.66	3.29	1.26
	WA2	0.87				3.18	1.27
	WA3	0.80				3.19	1.29
Perceived Concern	PC1	0.78	0.88	0.88	0.65	3.54	1.34
	PC2	0.84				3.23	1.24
	PC3	0.85				3.23	1.27
	PC4	0.74				3.29	1.34
Continued Participation Behavior Intention	BI1	0.86	0.89	0.89	0.73	3.20	1.24
	BI2	0.86				3.37	1.24
	BI3	0.84				3.37	1.29

Note: CR = Composite Reliability; AVE = Average Variance Extracted; SD = Standard Deviation

In ensuring that the constructs developed are distinct and substantively different from one another, the study evaluated the discriminant validity of the 7 constructs after examining convergent validity [122]. The criterion used to assess the discrimination validity was the standard proposed by [139]. This standard assert that a construct is valid when it demonstrates more variability among its own elements than with any other factor [122]. According to this criterion, for each construct, AVE should be larger than the square of the

absolute value of its correlation with other constructs. Table 10 confirms that this standard was satisfied, thereby indicating satisfactory discriminant validity.

Henseler et al. [141] utilized the heterotrait-monotrait correlation coefficients ratio (HTMT) and the variance-based method [139] to analyze discriminant validity in SEM research. Based on the HTMT ratio in Table 10, it was found that all results proved to be below the suggested threshold of 0.85, suggesting that no significant discriminant validity concerns were observed.

Table 10 Results of Discriminant Validity – Fornell-Larcker criterion of Measures and Correlation Matrix and HTMT analysis.

Construct	AVE	MSV	ASV	Inter-correlations and the square root of the AVEs (in bold) with HTMT analysis						
				EB	EI	EE	WA	BI	PC	HM
EB	0.73	0.39	0.26	0.853						
EI	0.72	0.41	0.28	0.625***	0.846					
EE	0.70	0.41	0.30	0.584***	0.641***	0.837				
WA	0.66	0.31	0.24	0.561***	0.496***	0.503***	0.811			
BI	0.73	0.34	0.25	0.485***	0.479***	0.568***	0.539***	0.855		
PC	0.65	0.19	0.13	0.359***	0.378***	0.347***	0.434***	0.320***	0.803	
HM	0.81	0.35	0.23	0.385***	0.534***	0.588***	0.405***	0.581***	0.331***	0.898

Notes: AVE = Average Variance Extracted; MSV= Maximum Shared Variance; ASV= Average Shared Variance; EB=Economic Benefit; EI= Esteem Influence; EE = Effort Expectancy; WA = Work Autonomy; BI = Continued Behavioral Intention; PC= Perceived Concern; HM= Hedonic Motivation. The values on the diagonal are the square roots of the AVE ($\sqrt{AVE}$); values below the diagonal are the inter-construct correlations (***) $p < 0.001$.

The second step in statistical assessment involves evaluating the fitness of the proposed models, which is crucial for validating relationships between variables [142]. Various absolute and relative fit indices, recommended by [143] and [144], are used. Absolute fit

coefficients, such as Chi-square/degree of freedom (CMIN/DF), root mean square error of approximation (RMSEA), and Standardized Root Mean Squared Residual (SRMR), evaluate the model's ability to replicate recorded data [122]. Relative fit parameters, like Comparative fit index (CFI) and Tucker-Lewis's coefficient (TLI), contrast the proposed model to a null model and determine if the relationships improve the fit [140, 145, 146]. [Table 11](#) presents the calculated values for these indices, all of which indicate an adequate model fit.

Table 11 Model fit indices

Indices	Measured value	Recommended values		Source
		Acceptable	Excellent	
CMIN	417.6			
DF	188			
CMIN/DF	2.22	$3.0 < \text{CMIN/DF} < 5.0$	$1.0 \leq \text{CMIN/DF} \leq 3.0$	[143, 147]
RMSEA	0.060	< 0.1	< 0.08	[122, 146]
SRMR	0.0487	< 0.1	< 0.08	[122, 146]
CFI	0.956	> 0.70	> 0.90	[140, 146]
TLI	0.945	> 0.80	> 0.90	[145]

Note: CMIN/DF: Chi-square/degree of freedom; RMSEA: root mean square error of approximation; SRMR: Standardized Root Mean Squared Residual; CFI: Comparative fit index; TLI: Tucker-Lewis's coefficient.

4.1.3 Structural Model Assessment

The SEM is employed to test the hypotheses within a structural framework, after confirming the measurement framework through CFA and exploratory factor analysis (EFA). The structural framework evaluation follows a similar process to the CFA. The final structural model is provided in [Appendix III](#). Path coefficients represent the

hypothesized connections between latent factors, ranging from -1 (strong negative connection) to +1 (strong positive connection) [148]. Values near these extremes are likely to have an insignificant commonality. Among our hypotheses, only H3, H4, and H5 showed significant positive relationships, while the others did not. A typical significance level is a p-value of 0.05, 0.01 or 0.001, indicating that the null hypothesis has a less than 5%, 1%, or 0.1% chance of being correct. If the p-value is greater than 0.05, the hypothesis is dismissed [149]. Our analysis revealed that only three hypotheses were positively significant. Specifically, the relationship between effort expectancy and continued behavioral intention (H3) was significant at $p < 0.05$. Additionally, Hedonic motivation and continued behavioral intention (H4), and work autonomy and continued behavioral intention (H5), showed highly significant correlations at $p < 0.001$. Conversely, the esteem influence did not exhibit statistical significance with a β value, which indicates to the strength the relationship between the independent and dependent variables in the standardized regression coefficient model, of -0.017 and $p > 0.1$, leading to the rejection of Hypothesis H1. In addition, the results did not support Hypothesis H2 since the impact between economic benefits and the intention to continue participating did not prove significant ($\beta = 0.114$, $p > 0.1$). Furthermore, perceived costs did not significantly and negatively affect the intent of couriers to continue participating in crowded jobs, with a β value of - 0.001 and $p > 0.1$. As a result, Hypothesis H6 was also rejected, as shown in [Table 12](#).

Table 12 Structural equation modelling outcomes

Hypothesis	Path	Path coefficient (β)	Proposed effect	Significance (p-value)	Finding
H1	EI → BI	- 0.017	+	0.807	not supported
H2	EB → BI	0.114	+	0.107	not supported
H3	EE → BI	0.186	+	< 0 .05	supported
H4	HM → BI	0.314	+	< 0.001	supported
H5	WA → BI	0.284	+	< 0.001	supported
H6	PC → BI	- 0.001	-	0.991	not supported

Note: EI= Esteem Influence; EB = Economic Benefit; EE = Effort Expectancy; HM= Hedonic Motivation; WA = Work Autonomy; PC= Perceived Concern; BI = Continued Behavioral Intention.

According to [150], the percentage of variances in the dependent variable that can be calculated by the independent variables (R^2) ranges from 0 to 1, with 1 indicating the best prediction accuracy. Our study finds that collectively, all factors explain 0.48 of the variance in behavioral intention showing that the generated model has a good explanatory ability [151].

In a second step, the variables “gender,” “age,” “occupation,” “income”, and “type of job” were controlled for in relation to continued behavioral intention. All these variables were found to be statistically insignificant except for the type of job ($\beta = 0.153$, $p < 0.05$) (see [Table 13](#)).

Table 13 Control variables for SEM analysis

Path	Path coefficient (β)	Significance (p-value)
Gender → BI	0.111	0.067
Age → BI	0.086	0.386
Occupation → BI	0.049	0.363
Income → BI	0.070	0.921
Type of job → BI	0.076	0.021 < 0.05 (supported)

Note: BI = Continued behavioral intention

4.1.4 Common Method Bias (CMB)

This study involves data collection through surveys, introducing the potential for Common Method Bias (CMB). CMB can affect the observed relationships between variables, potentially introducing bias into the results. As a result, the possibility of such bias in respondents' answers cannot be entirely ruled out [152]. We followed two main strategies to reduce this risk, namely, methodological and statistical [153]. Methodologically, we concentrated on simplifying survey questions through pre-testing and pilot testing, ensuring respondent anonymity to encourage honest responses, and utilizing online and paper-based surveys. These steps align with best practices highlighted in earlier studies [154, 155] to minimize response bias and enhance the collected data's overall validity.

Statistically, we applied Harman's Single Factor Test in SPSS 26.0, which showed that the largest single factor accounted for 38.79% of the variance, well below the 50% threshold, indicating CMB was not a significant issue [153]. We also conducted a Common Latent Factor (CLF) test, comparing standardized regression weights with and without the CLF. The results showed less than 20% differences in all relationships, except for one instance, where the difference was 31%, which indicates that CMB is not a major problem [156]. In addition, we used a post-hoc marker variable test [157], with Timestamp as an unrelated variable, to check for Common Method Bias (CMB) [155, 158]. Further analysis of fit indices, such as CFI, RMSEA, SRMR, and TLI showed that the impact of CMB is negligible as the CFI value increased from 0.956 to 0.958, RMSEA changed from 0.060 to 0.057, SRMR rose from 0.0487 to 0.50, and TLI remained unchanged at 0.945, which demonstrates a very small change. Adding the marker variable to the model did not lead to

any noticeable changes in path coefficients or the significance of the hypothesized relationships, indicating that CMB is not a concern in this study. [Table 14](#) shows the structural model estimates before and after the CMB adjustment.

4.1.5 Multi-collinearity and autocorrelation test

We checked for multi-collinearity and autocorrelation using a few key tools: Durbin-Watson, tolerance, and Variance Inflation Factor (VIF) statistics to capture the dependencies among the independent variables in multiple linear regression model [155]. A Durbin-Watson score between 1.5 and 2.5 usually indicates that autocorrelation is not an issue, meaning the residuals are independent [159]. Regarding multi-collinearity, VIF values greater than 5 and tolerance values below 0.2 [160], or VIF values over 10 and tolerance dropping below 0.1 [161], would indicate a potential problem between the predictors. However, as seen in

[Table 15](#), all the values are within acceptable ranges, indicating that the model is clear of both multi-collinearity and autocorrelation issues ([see Appendix V](#)).

Table 14 Path coefficients before and after CMB adjustment

Hypothesis	Path	Original Estimates (β)	Original Significance (p-value)	CMB Adjusted Estimates (β)	Adjusted Significance (p-value)
H1	EI → BI	- 0.017	0.807	-0.023	0.749
H2	EB → BI	0.114	0.107	0.138	0.056
H3	EE → BI	0.186	*	0.190	*
H4	HM → BI	0.314	***	0.301	***
H5	WA → BI	0.284	***	0.293	***
H6	PC → BI	- 0.001	0.991	0.001	0.979

Notes: *p < 0.05; **p < 0.01; ***p < 0.001.

Table 15 Multi-collinearity test.

CONSTRUCTS	Durbin-Watson	Tolerance	VIF
EI	1.995	0.525	1.906
EB		0.581	1.723
EE		0.532	1.878
HM		0.665	1.505
WA		0.645	1.551
PC		0.788	1.270

4.1.6 Endogeneity test

In this study, checking for endogeneity was essential to ensure accurate, reliable results [162]. Endogeneity can occur when an unobserved factor affects both the independent variables and the outcome, Behavioral Intention (BI). To address this, we conducted a Two-Stage Least Squares (2SLS) analysis in Stata/SE 18.5 [155, 163, 164], using three core tests: the endogeneity test, the weak instrument test, and the over-identification test. We specifically evaluated each predictor—EI, EB, EE, HM, WA, and PC—to confirm whether any of these had an unwanted correlation with the error term. Results from these tests are outlined in Table 16.

Table 16 Endogeneity Test Using 2SLS

Dependent Variable	Endogenous variable (Instrumented)	Test of Endogeneity				First-stage regression summary statistics			Tests of overidentifying restrictions			
		Durbin (score)	value	Wu-Hausman	P-value	Partial R-square	F-statistics	P-value	Basman	P-value	Sargan (score)	P-value
BI	EI	0.216	0.643	0.2107	0.647	0.1484	167.29	0	2.9613	0.0853	2.9177	0.088
	EB	0.737	0.391	0.721	0.396	0.3218	207.6	0	5.882	0.053	5.828	0.054
	EE	1.381	0.240	1.354	0.245	0.2455	182.08	0	4.787	0.091	4.728	0.094
	HM	1.923	0.166	1.889	0.170	0.1303	143.78	0	3.784	0.151	3.726	0.155
	WA	2.331	0.127	2.292	0.131	0.0807	143.40	0	3.317	0.190	3.262	0.196
	PC	2.848	0.092	2.805	0.095	0.0607	94.7	0	1.893	0.595	1.847	0.605

Our findings indicate that endogeneity is not a concern in this model. The Durbin and Wu-Hausman tests, with p-values consistently above 0.05, show that endogeneity is not statistically significant across the variables. The Partial R-square and F-statistics for each instrumented variable are sufficiently high, and the p-values are significant, indicating that the instruments used are strong and relevant to this analysis. Finally, the non-significant p-values from the Sargan and Basmann tests confirm that the instruments are valid fitting well with the exogenous variables in our model. This combination of tests reassures us that endogeneity does not interfere with the integrity of our results, allowing us to proceed with confidence.

4.1.7 Multigroup Analysis

To explore how demographic factors influence the continued participation behavioral intention, we grouped participants based on "gender", "age", "occupation", "income", and "type of job". Gender was categorized as male or female. Age was divided into three groups: 18-25, 26-35, and over 35. Occupation had four groups: student, employed, self-employed, and others. Income was divided into less than 2000 SAR, 2000-5000 SAR, and over 5000 SAR. Lastly, the type of preferred job was separated into Occasional, Committed, and Non to do it.

A multigroup analysis was conducted with SPSS Amos 26.0 to compare structural models across different groups(see [Table 17](#)) . The findings show that demographic factors play a crucial role in determining the relationship between EB, EE, HM, and WA with BI. In the multigroup analysis results, gender difference shows that financial motivations (H2)

mainly drive male couriers, while work autonomy (flexibility) (H5) for female couriers is far more appealing. In terms of age, younger and older couriers value ease of use (H3), enjoyment (H4), and job autonomy (H5). In contrast, 26–35 years old value ease of job (H3) and enjoyment (H4) but do not emphasize work autonomy (H5), possibly due to their stage of career development where structured roles are preferred. For occupation, self-employed couriers respond to multiple motivators, including ease of use(H3), enjoyment (H4), and work autonomy (H5), while students and employed individuals emphasize enjoyment(H4) and flexibility (H5). Regarding income, significant relationships or ease of use (H3), enjoyment (H4), and work autonomy (H5) were found for those earning less than 2000 SAR and over 5000 SAR. However, only enjoyment (H4) and work autonomy (H5) were significant for participants earning between 2000-5000 SAR. Lastly, the type of job group showed that occasional and non-preferred delivery participants focused most significantly on enjoyment (H4) and autonomy (H5), while committed couriers prioritized economic benefit (H2), ease of use (H3), and enjoyment (H4). These findings underline that each demographic group is motivated by different factors, guiding strategies to enhance courier retention through targeted financial incentives, ease of use, enjoyment, and job autonomy.

This approach helps determine if there are variations in the structural model between these groups [165]. The male group showed a significant relationship for economic benefit, hedonic motivation, and work autonomy with continued behavioral intention. The female group demonstrated a significant relationship only for work autonomy.

The findings show that demographic factors play a crucial role in determining the relationship between EB, EE, HM, and WA with BI. In the multigroup analysis results,

gender difference shows that financial motivations (H2) mainly drive male couriers, while work autonomy (flexibility) (H5) for female couriers is far more appealing. In terms of age, younger and older couriers value ease of use (H3), enjoyment (H4), and job autonomy (H5). In contrast, 26–35 years old value ease of job (H3) and enjoyment (H4) but do not emphasize work autonomy (H5), possibly due to their stage of career development where structured roles are preferred. For occupation, self-employed couriers respond to multiple motivators, including ease of use(H3), enjoyment (H4), and work autonomy (H5), while students and employed individuals emphasize enjoyment(H4) and flexibility (H5). Regarding income, significant relationships or ease of use (H3), enjoyment (H4), and work autonomy (H5) were found for those earning less than 2000 SAR and over 5000 SAR. However, only enjoyment (H4) and work autonomy (H5) were significant for participants earning between 2000-5000 SAR. Lastly, the type of job group showed that occasional and non-preferred delivery participants focused most significantly on enjoyment (H4) and autonomy (H5), while committed couriers prioritized economic benefit (H2), ease of use (H3), and enjoyment (H4). These findings underline that each demographic group is motivated by different factors, guiding strategies to enhance courier retention through targeted financial incentives, ease of use, enjoyment, and job autonomy.

Table 17 Multigroup path analysis

Hypothesis	Path	Group Gender		Group age			Group occupation			Group income			Group type of job			
		Male (255)	Female (90)	18-25 (187)	26- 35 (110)	>35 (48)	Student (190)	Employed (65)	Self- employed (29)	Other (61)	<2000 (181)	2000-5000 (112)	>5000 (52)	Occasional (151)	Committe d (141)	Non (53)
H1	E $\rightarrow$ BI															
H2	EB $\rightarrow$ BI	0.007<0.01 significant													0.026 <0.05 significant	
H3	EE $\rightarrow$ BI			0.007< 0.01 significant	0.018< 0.01 significant	0.007< 0.01 significant	0.017< 0.05 significant				0.041< 0.05 significant		0.041< 0.05 significant		0.004 <0.01 significant	
H4	HM $\rightarrow$ BI	<0.001 significant		<0.001 significant	0.007<0.01 significant	<0.001 significant	<0.001 significant	0.091 <0.05 significant	<0.001 significant	<0.001 significant	<0.001 significant	0.002< 0.01 significant	<0.001 significant	<0.001 significant	<0.001 significant	<0.001 significant
H5	WA $\rightarrow$ BI	.024<0.05 significant	0.007<0.01 significant	<0.001 significant		<0.001 significant	0.005<0.01 significant	0.034 <0.05 significant	0.005<0.01 significant	0.005<0.01 significant	0.001 ≤0.001 significant	0.036 <0.05 significant	<0.001 significant	<0.001 significant		<0.001 significant
H6	PC $\rightarrow$ BI															

Note: H=Hypothesis; E|= Esteem Influence; EB = Economic Benefit; EE = Effort Expectancy; HM= Hedonic Motivation; WA = Work Autonomy; PC= Perceived Concern; BI = Continued Behavioral Intention

CHAPTER 5

DATA ANALYSIS AND RESULTS OF REQUEST ACCEPTANCE PROBABILITY MODEL

5.1 Data Analysis and Results of Request Acceptance Probability Model

As outlined in Section 4.1.1, after excluding invalid or incomplete submissions, we obtained 345 valid questionnaires. These questionnaires encompass 6210 (345×18) data samples in Saudi Arabia, as discussed in Section 3.2.3. [Table 8](#) details the descriptive statistics for the data collected from October 2023 to March 2024 in Saudi Arabia. The survey data indicates our data is balanced, with 52% of requests being accepted by (couriers) participants, while 48% were rejected.

To analyze the demographic control variables of our study, we employed Logistic Regression with Maximum Likelihood Estimation (MLE) for feature selection, as it provides a statistically rigorous technique for identifying key predictors using p-values and coefficients. Using the Statsmodels library in Python, we investigated significant factors from control variables, such as gender, age, income, occupation, and type of job, alongside quantitative (stated preference) attributes like compensation, distance, and delivery time as independent factors, and the output variable indicating acceptance or rejection, as outlined in Table 7. We have identified gender, type of job, compensation, distance, and delivery time as significant factors. These five variables serve as inputs to model the acceptance of

tasks, with the output being either acceptance or rejection of the task. All our computations were conducted on a computer featuring a 13th Gen Intel Core i7 8-core CPU with 16 GB of RAM, operating at 2.2 GHz, and using Windows 11. The computation was carried out using Python version 3.10.12. We employed Python as the programming language for the experimental setup and tested using TensorFlow/Keras, Scikit-learn, XGBoost, Pandas, Numpy, and Matplotlib libraries. The detailed hardware and software specifications are shown in [Table 18](#).

Table 18 Software Specifications for Models Implementation

CPU	Processor	Model	Generation
	Intel Core i7, 8-core(2.2 GHz)	K3504VA	13th Gen
RAM	16 GB		
OS	Windows 11 Home Single Language - 64bit		
Language	Python ,Version 3.10.12		
Software	Statsmodels= LR and feature selection (significant factor analysis).		
	pandas= Data manipulation and analysis.		
	numpy= Numerical operations and array handling.		
	Matplotlib= Data visualization (bar plots).		
	Scikit-learn= Classic ML models (LR, DT, SVM), ensemble learning models (RF, Voting Classifier), and metrics.		
	TensorFlow/Keras= Deep learning models (ANN, LSTM, GRU, AlexNet).		
	XGBoost= Gradient boosting machine learning algorithm.		

Upon analyzing the control variables, we found only gender ($B = -0.276$, $p < 0.05$) and type of job ($B = -0.1224$, $p < 0.05$) to be significant. Additionally, the quantitative variables were also significant: cost ($B = 0.168$, $p < 0.001$), distance ($B = -0.1143$, $p < 0.001$), and delivery time delivery ($B = -0.1798$, $p < 0.001$). These findings highlight that demographic factors and stated preference attributes are crucial in influencing task acceptance decisions.

[Table 19](#) provides a detailed summary of the estimated values for the control variables,

which includes coefficients, standard errors, Z-values, and p-values. To visualize how these variables affect tasks acceptance, a 3D scatter plot illustrates how acceptance (Output = 1) and rejection (Output = 0) vary with compensation, distance, time, as shown in [Figure 15](#). The left plot at a higher compensation, shorter distances, and minimal times shows high acceptance rates (up to 99.7%). In contrast, the right plot indicates that longer distances and longer time demonstrate high rejection rates (over 90 %) at lower compensation. These trends highlight the importance of distance, time, and compensation-effectiveness affecting courier acceptance decisions. Furthermore, for feature impact on acceptance, [Figure 16](#) shows that delivery time and distance negatively impact task acceptance (a negative correlation), while higher compensation positively influences it (positive correlation). This suggests participants prefer tasks with shorter times and distances and are more likely to accept tasks with higher compensation.

Table 19 Estimation Result for control variables

Optimization terminated successfully.						
Current function value: 0.294049						
Iterations 8						
Logit Regression Results						
Dep. Variable:	Output	No. Observations:	6210			
Model:	Logit	Df Residuals:	6201			
Method:	MLE	Df Model:	8			
Date:	Tue, 03 Dec 2024	Pseudo R-squ.:	0.5750			
Time:	23:35:21	Log-Likelihood:	-1826.0			
converged:	True	LL-Null:	-4296.7			
Covariance Type:	nonrobust	LLR p-value:	0.000			
	coef	std err	z	P> z	[0.025	0.975]
const	5.5541	0.333	16.660	0.000	4.901	6.207
Gender	-0.2760	0.098	-2.805	0.005	-0.469	-0.083
Age	-0.0090	0.076	-0.119	0.905	-0.158	0.140
Occupation	-0.0608	0.044	-1.376	0.169	-0.147	0.026
Income	-0.0934	0.065	-1.437	0.151	-0.221	0.034
Type-of-Job	-0.1224	0.061	-2.015	0.044	-0.241	-0.003
Compensation	0.1681	0.007	25.803	0.000	0.155	0.181
Distance	-0.1143	0.009	-12.800	0.000	-0.132	-0.097
Time	-0.1798	0.004	-40.745	0.000	-0.188	-0.171

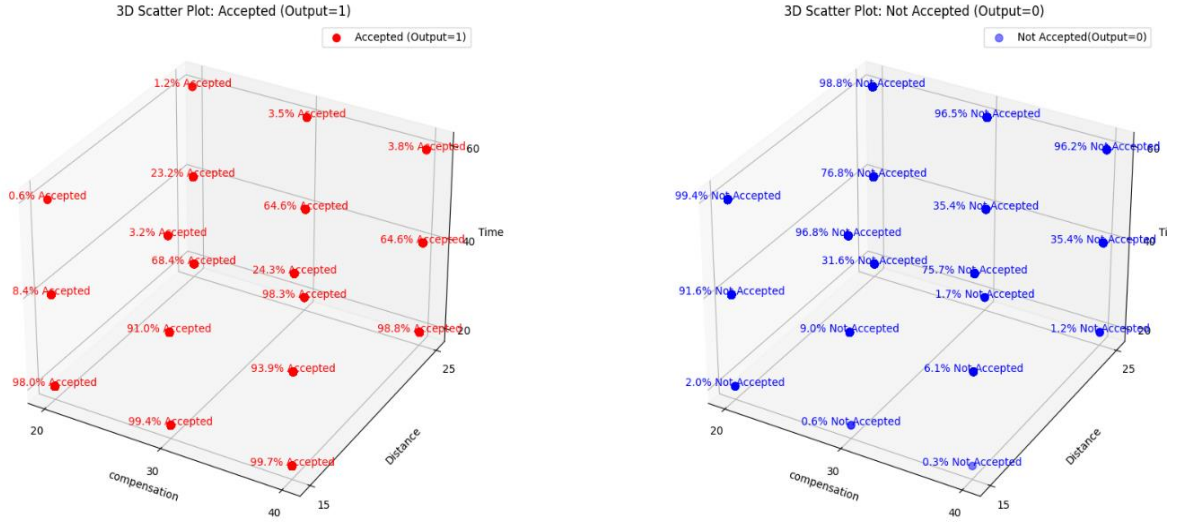


Figure 15 3D scatter plot for acceptance or reject tasks

To examine this further, we compared actual data with various ML techniques and assessed the performance of each model using several metrics, including prediction accuracy, precision, recall, and F1-Score. Accuracy serves as a fundamental criterion for evaluating the overall predictive capability of a model. Precision measures the percentage of positive class forecasts, such as accepting delivery tasks, correctly categorized as positive. Recall, also known as sensitivity, indicates the proportion of true positives correctly identified. The F1-Score, an unbiased evaluation metric, is calculated by considering the harmonic means of recall and precision. These metrics are commonly employed to evaluate the effectiveness of ML models in predictive analysis [166, 167].

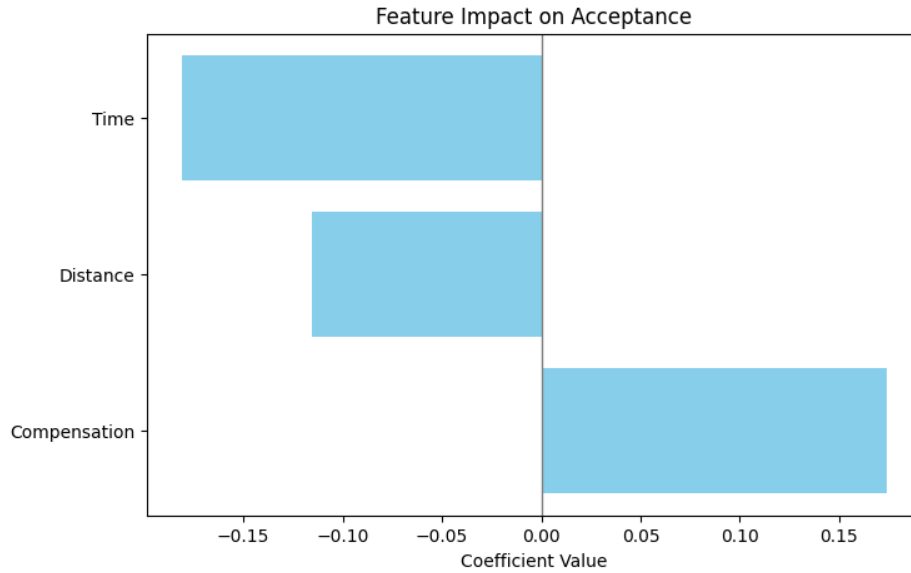


Figure 16 Feature impact on acceptance

We allocated 80% of the data for training and 20% for testing to fine-tune and evaluate our model parameters, respectively. The evaluation of accuracy metric in Figure 17 shows that all ten ML models, except LR, achieved accuracy rates above 90%. Several models, including ANN, DT, SVM, XGBoost, GRU, AlexNet, and Soft Voting, achieved the highest accuracy of 91.06%. RF and LSTM performed slightly lower at 90%, while LR recorded the lowest accuracy at 89.05%. The results highlight each technique's varying strengths and weaknesses in predicting delivery task acceptance. These findings emphasize the effective use of five predictors—gender, type of job, compensation, distance, and delivery time—in modeling task acceptance behavior. By comparing the accuracies of these models, we demonstrate the value of advanced techniques, such as deep learning methods (e.g., ANN, SVM, GRU, and AlexNet) and ensemble methods (e.g., XGBoost and Soft Voting), in improving predictive accuracy and optimizing delivery task

assignments. These insights are crucial for refining predictive modeling approaches in logistics.

The precision score from various models of ML in [Figure 18](#) highlights insights into the model's performance characteristics. Logistic regression (LR) achieved the highest precision score of 91.54%. At the same time, other models, including RF, ANN, DT,

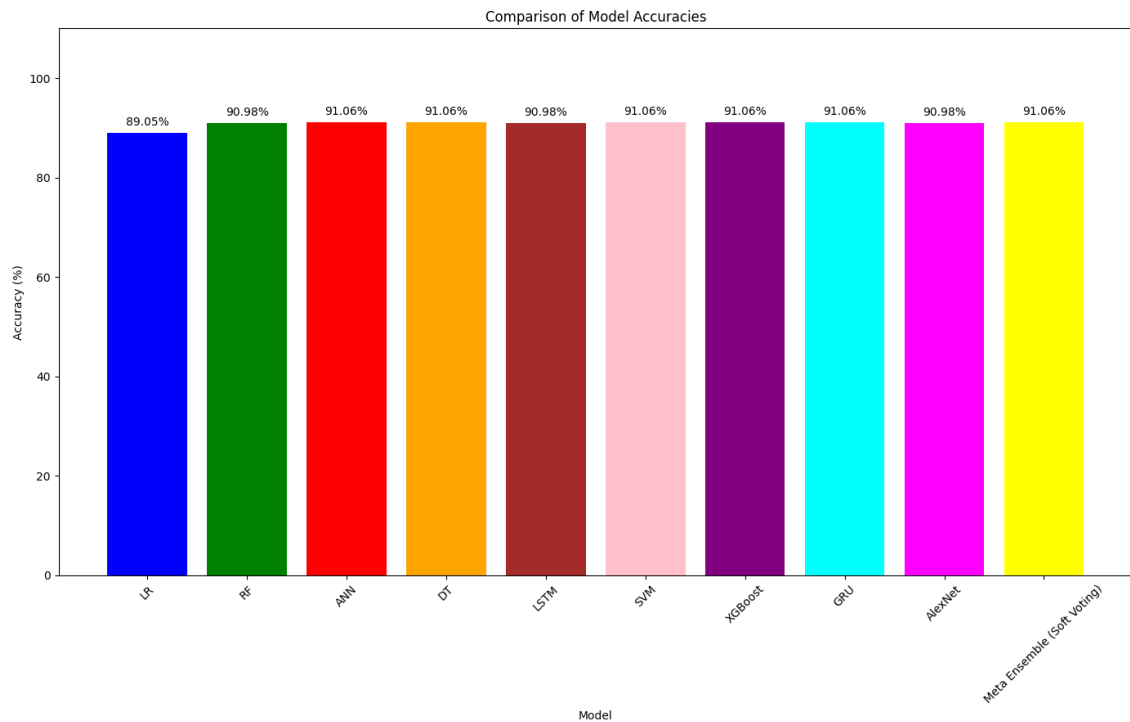


Figure 17 Comparison of model accuracies

LSTM, SVM, XGBoost, GRU, Lx NET, and Meta Ensemble (Soft Voting), also reached a precision level of about 89.97% or 89.71%, showing similar performance with a bit lower results. The above results show that, although LR outperforms the other ML models in precision metric, the different models provide stable predictive accuracy. All models performed well, as can be inferred from the high precision scores; however, LR was the most precise according to this evaluation.

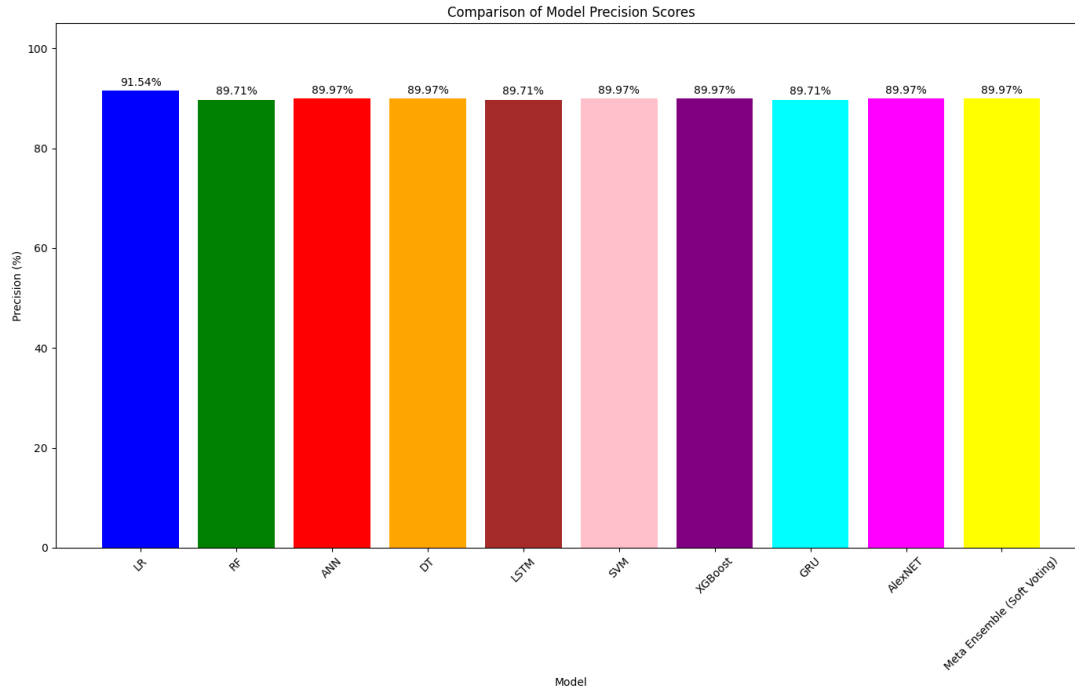


Figure 18 Comparison of model precision scores

Figure 19 offers a comparison of recall scores across different ML models. It shows that XGBoost achieved the highest recall scores at 96.70%, showcasing its exceptional ability to handle our data. Models such as RF, ANN, LSTM, GRU, and AlexNet achieve recall scores of 93.09%, demonstrating strong predictive capabilities, followed by DT, SVM, and Soft Voting with scores of 92.94%, indicating consistent reliability. Logistic Regression (LR), with the lowest score at 86.66%, highlights limitations in handling complex patterns. Overall, XGBoost emerges as the most effective model, while others still show robust performance.

Figure 20 shows the highest F1-score for ANN at 91.46%, indicating its highest potential in properly balancing recall and precision. Moreover, all models, except Logistic Regression (LR), show F1-Score above 90%, which further indicates the very strong

potential of most models for performing tasks that require a good balance between false positives and negatives. Logistic Regression (LR) shows the lowest F1-score of 89.03%, which has some limitations in this balance. These results emphasize that while all models perform reliably, ANN has a slight edge in achieving optimal classification balance.

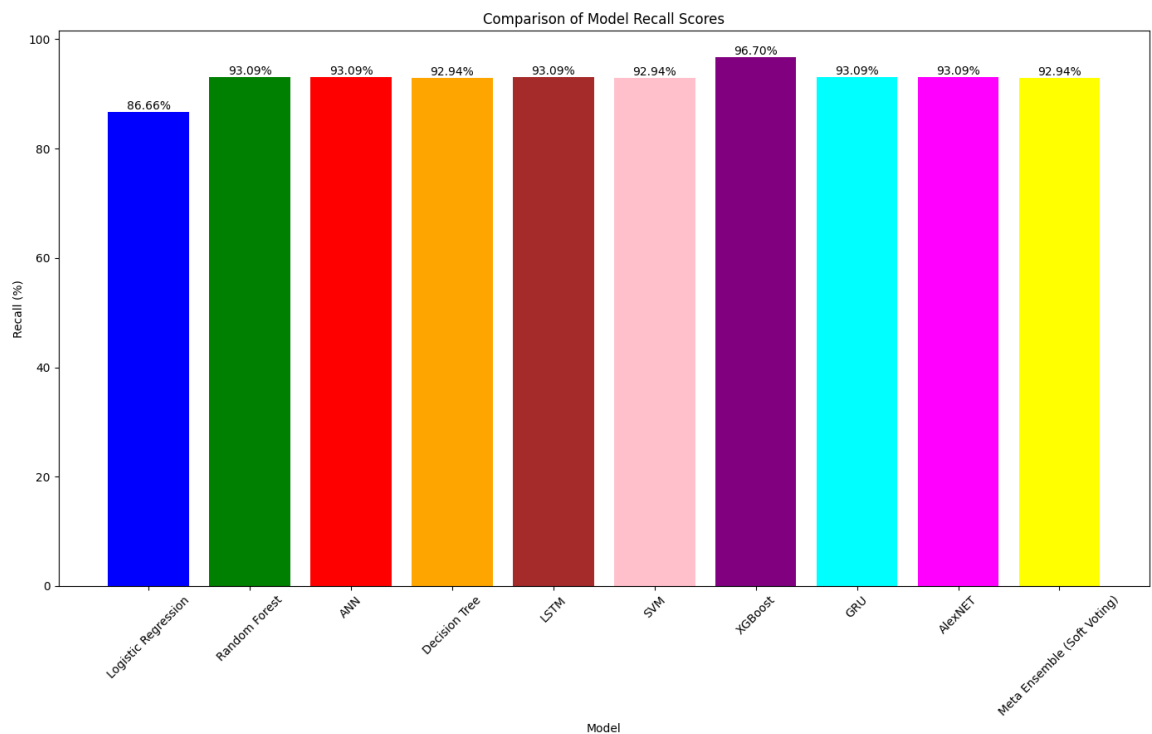


Figure 19 Comparison of model recall scores

In summary, the analysis of accuracy, precision, recall, and F1-score highlight the strengths of machine and deep learning models in predicting delivery task acceptance, as summarized in [Table 20](#) and visually illustrated in [Figure 21](#). ANN, Decision Tree (DT), SVM, XGBoost, GRU, AlexNet, and Soft Voting achieve the highest accuracy at 91.06%, while Logistic Regression (LR) trails at 89.05%. LR excels in precision with 91.54%,

though ANN and other models maintain strong precision at 89.97%. XGBoost leads in recall with 96.70%, followed by ANN and others at 93.09%. ANN achieves the highest F1-score at 91.46%, making it the most balanced and versatile model across precision and recall, while XGBoost and others follow closely at 91.43%.

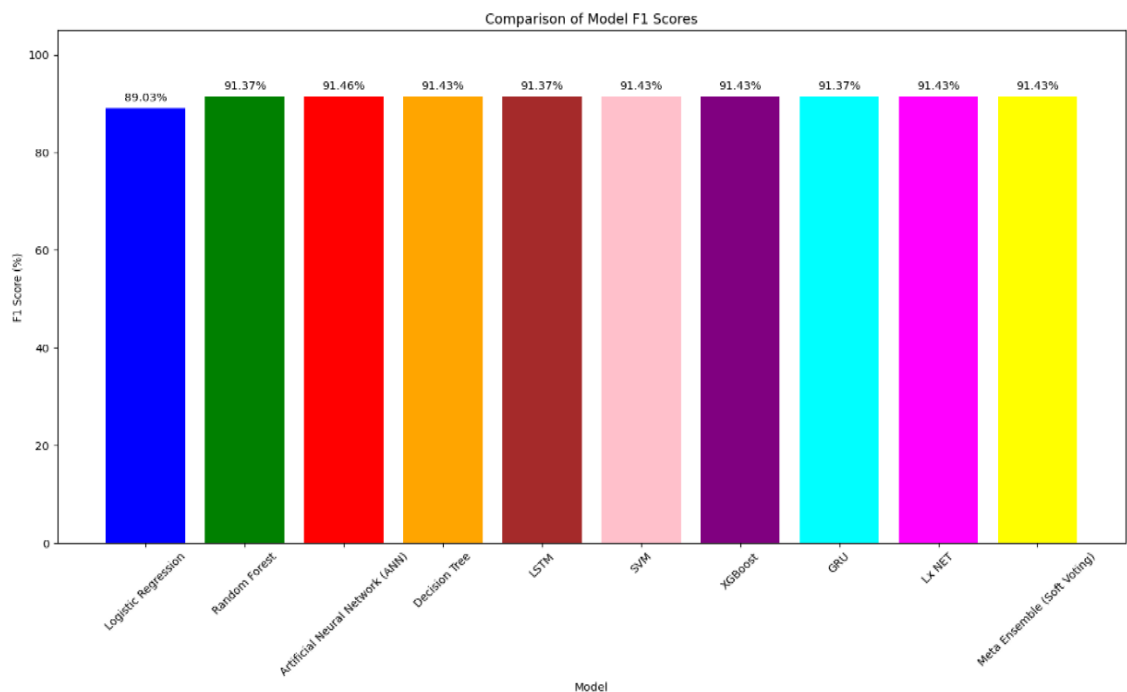


Figure 20 Comparison of model F1-score

Overall, XGBoost and ANN stand out as the most robust model, given its consistently strong performance across all metrics, making it ideal for future research in prediction, optimization, and scheduling tasks. Soft Voting, AlexNet, GRU, DT, and SVM also demonstrate reliable performance, particularly in scenarios requiring balanced metrics. Random Forest (RF), and LSTM demonstrate suitable predictive models for applications requiring high recall and sensitivity, while LR stand out in precision. These findings underscore the effectiveness of advanced machine and deep learning techniques in enhancing task acceptance and decision-making in last-mile delivery logistics.

Table 20 ML models and prediction results

ML Technique	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
LR	89.05	91.54	86.66	89.03
RF	90.98	89.71	93.09	91.37
ANN	91.06	89.97	93.09	91.46
DT	91.06	89.97	92.94	91.43
LSTM	90.98	89.71	93.09	91.37
SVM	91.06	89.97	92.94	91.43
XGBoost	91.06	89.97	96.70	91.43
GRU	91.06	89.71	93.09	91.37
AlexNet	91.06	89.97	93.09	91.43
Soft Voting	91.06	89.97	92.94	91.43

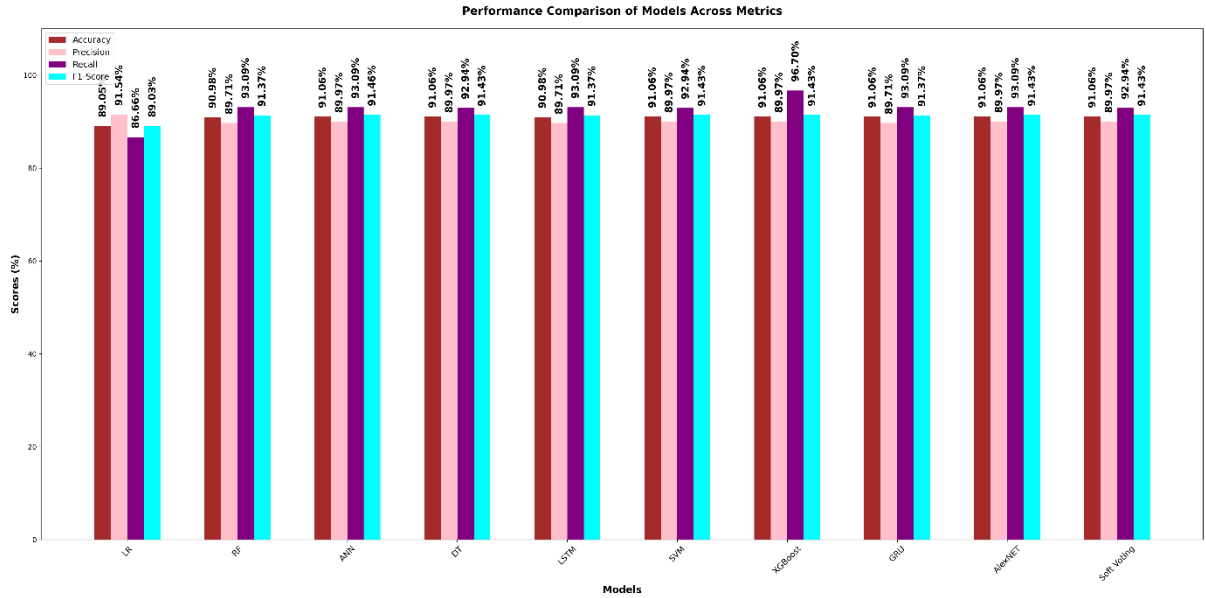


Figure 21 Comparing models' metrics

5.2 Sensitivity Analysis and Results of Request Acceptance Probability Model

We initially examined the sensitivity of the original data (6,210 samples) using logistic regression, which efficiently classifies acceptance percentages depending on compensation, distance, and time. As shown in Figure 23 and Figure 22, the data highlight important trends: for shorter delivery intervals (20 minutes), acceptance remains consistently high (>98%) throughout 15 km and 25 km distances, demonstrating low sensitivity compensation. Acceptance demonstrates considerable sensitivity for 40 minutes, stabilizing at 93.9% at 15 km and 64.6% at 25 km, with a notable threshold impact around 30 SAR and 20 SAR, respectively. At 60 minutes, acceptability is very sensitive to compensation and distance, gradually increasing to 24.3% at 50 SAR for 15 km but just 3.8% at 40 SAR for 25 km. This research reveals how time and distance dramatically affect the compensation sensitivity.

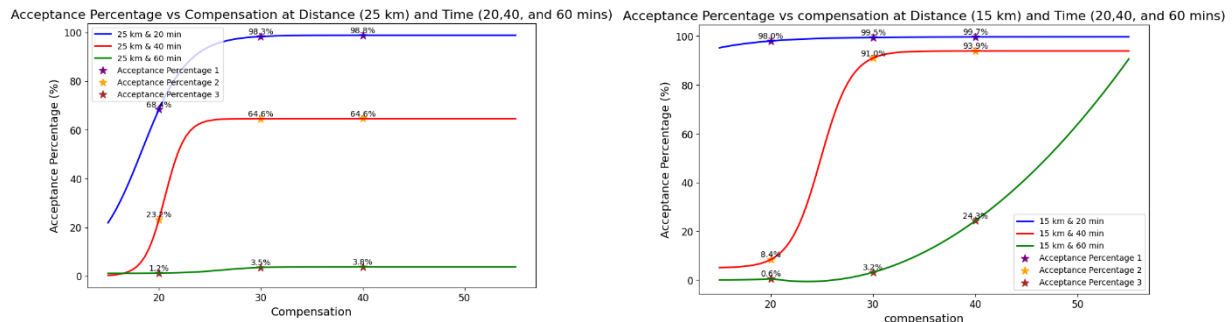


Figure 22 Logistic Regression curves for the probability of acceptance vs compensation at distance(25km) and time(20,40,60 min)

Figure 23 Logistic Regression curves for the probability of acceptance vs compensation at distance(15km) and time(20,40,60 min)

To further evaluate the robustness of the acceptance probability model, we conducted a sensitivity analysis by expanding the dataset from 6,210 to 40,000 samples using the Synthetic Minority Oversampling Technique for Nominal and Continuous features

(SMOTENC) while introducing slight noise to continuous features (e.g., compensation, distance, and time) to increase the variability in the data. [Figure 26](#), [Figure 27](#), and [Figure 25](#) illustrate how compensation, distance, and time have influenced the task acceptance outcomes after dataset expansion. On the expended dataset, as shown in [Figure 26](#), accepted cases (in red) are clustered to high- compensation values and short time because those outcomes significantly increase the likelihood of acceptance. On the other hand, not accepted (reject) cases (in blue) tend to be more common at lower compensation and longer time ranges. [Figure 25](#) and [Figure 27](#) further demonstrate that higher task acceptance (Output = 1) is associated with favorable conditions such as higher compensation and shorter times. In contrast, rejection (Output = 0) occurs predominantly at lower compensation and longer times. Although the 3D scatter plots suggest that distance has a similar distribution for both outcomes, the SHAP plot, as shown in [Figure 24](#), highlights its critical role in the model's predictions, indicating the compensation, time, and distance are most key factors influencing on the acceptance, while type of job, and gender have less effect on the models' predictions. Following this analysis, the performance of ten ML models was evaluated across four metrics: accuracy, precision, recall, and F1-score.

As shown in [Table 21](#) and [Figure 28](#), Random Forest (RF) emerged as the best-performing model, with the highest accuracy (95.60%), precision (95.79%), recall (95.46%), and F1-score (95.63%), demonstrating its overall superiority. XGBoost followed closely, excelling in recall (96.35%) and achieving high scores in other metrics, demonstrating its strength in correctly identifying positive outcomes. Combining predictions from multiple models, Soft Voting showed robust and adaptable performance with an accuracy of 94.84% and an F1-score of 94.89%. Decision Tree (DT) achieved a competitive accuracy of 92.94% and a

well-balanced F1-score of 93.00%, making it a reliable choice for simpler, effective classification tasks. Among deep learning models, GRU delivered strong results with a recall of 91.96% and an F1-score of 90.49%, slightly outperforming ANN, which achieved an F1-score of 90.22%. LSTM showed comparable results, emphasizing its suitability for sequential data. Decision Tree (DT) balanced simplicity and effectiveness, achieving a high F1-score (93.00%) and accuracy (92.94%), while Logistic Regression (LR) provided interpretable results with competitive precision (86.17%). Other models like SVM and Lx NET demonstrated moderate performance, suitable for specific applications.

Overall, these results highlight the effectiveness of advanced ML models, particularly RF,

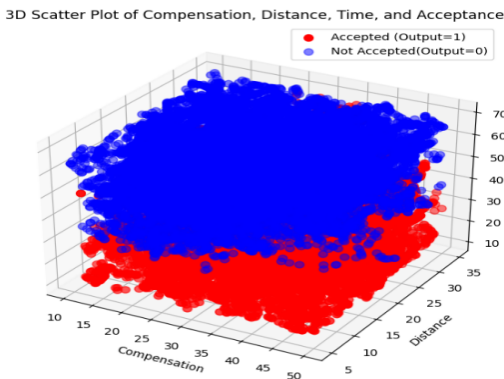


Figure 26 3D scatter plot of compensation, distance, time and output

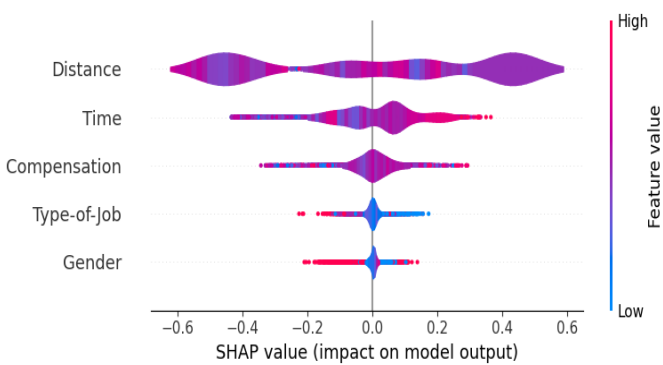


Figure 24 SHAP value impact features on model output

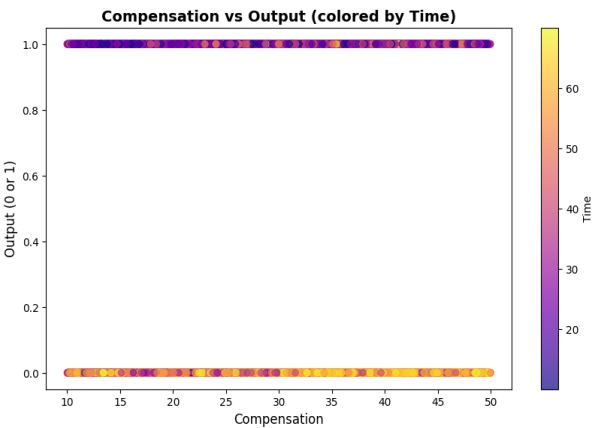


Figure 25 Impact input features (compensation and time) on output

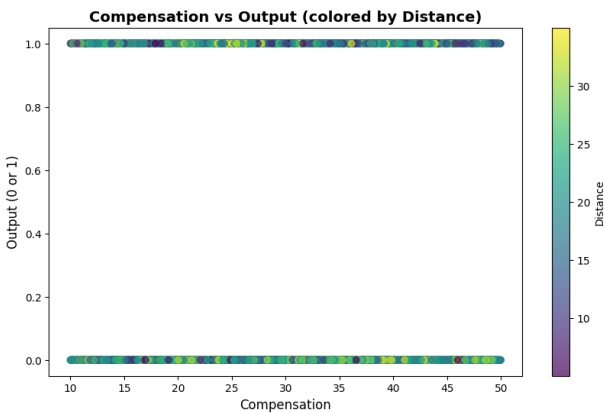


Figure 27 Impact input features (compensation and distance) on output

XGBoost, and Soft Voting, in predicting task acceptance. ANN and sequential models (LSTM and GRU) remain viable options for scenarios requiring robust generalization, while LR and DT offer interpretable and practical solutions. The use of SMOTENC to augment the dataset significantly enhanced model performance, reaffirming the importance of addressing data variability for improved predictive outcomes in last-mile delivery logistics.

Table 21 ML models and sensitivity analysis results

ML Technique	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
LR	84.90	86.17	83.43	84.78
RF	95.60	95.79	95.46	95.63
ANN	89.85	90.34	89.78	90.22
DT	92.94	92.86	93.15	93.00
LSTM	90.24	90.07	91.10	90.18
SVM	86.20	85.88	86.90	86.36
XGBoost	95.49	95.74	96.35	95.51
GRU	89.85	91.36	91.96	90.49
AlexNet	87.07	86.27	88.94	87.22
Soft Voting	94.84	94.60	93.58	94.89

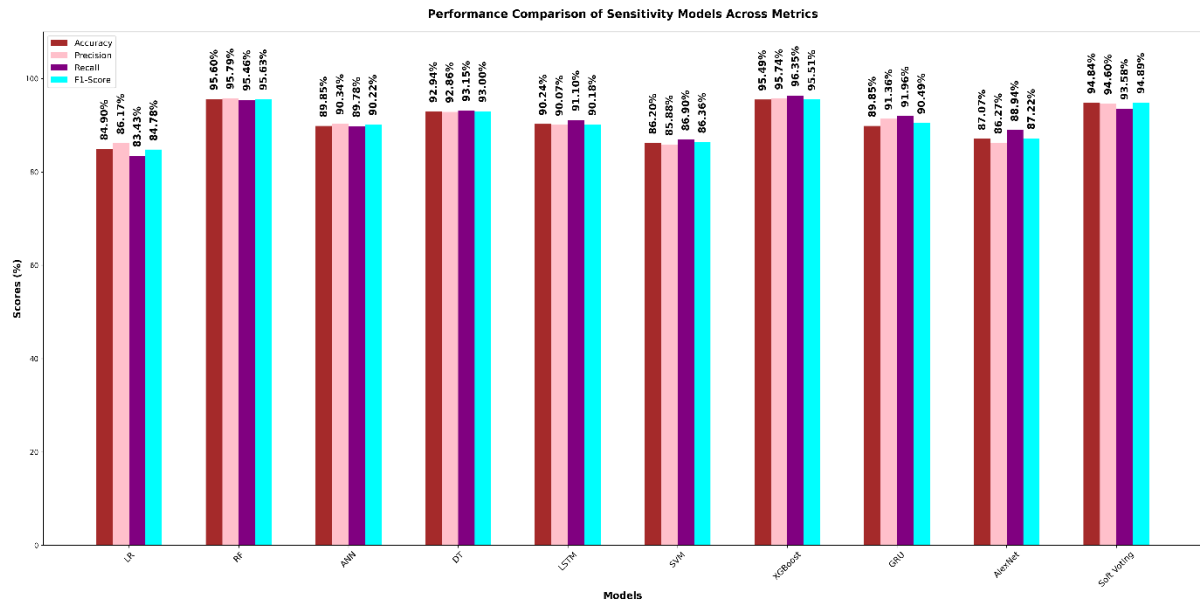


Figure 28 Performance comparison of sensitivity analysis models' metrics

CHAPTER 6

DISCUSSION AND IMPLICATIONS OF THE RESEARCH

6.1 Discussion of Continued Couriers' Behavioral Intention Model

Crowdsourcing platforms' success in generating value for companies depends on the availability of a large and capable workforce. However, it is difficult for these platforms to attract and retain skilled couriers. As a result, researchers and industry professionals are keen on understanding ways to promote courier involvement in crowdsourcing delivery [85, 168]. Relying on SETM, UTAUT2, and other relevant studies on the topic, we developed and evaluated a model that explains couriers' continued involvement in crowdsourcing. Our survey respondents generally had a neutral attitude towards the courier's continuous participation in crowdsourced last-mile delivery. Specifically, the mean evaluations of continued behavioral intention toward courier's willingness did not reach a rating of 4 or higher on a five-point Likert scale (see [Table 9](#)). This result is consistent with research [169], suggesting that individuals often need time to establish their opinions on emerging technologies. Therefore, it is essential to investigate the ongoing acceptance and participation in crowdsourced last-mile delivery at an early stage. This will

provide insights to guide its development and ultimately promote acceptance in its initial phases.

Our study found that factors like effort expectancy, hedonic motivation, and work autonomy significantly influence couriers' sustained participation. However, variables such as esteem influence, economic benefit, and perceived concern showed weak significance. Notably, economic benefit did not have a significant overall influence on courier participation, but it was significant in the group analysis of male couriers. Additionally, the effect of job type was significant in our study.

Initially, the significance of Esteem Influence in predicting couriers' acceptance of continuous participation in crowdsourced last-mile delivery was suggested (H1). Our hypothesis was not supported by the relationship we found between couriers' continuous participation and their esteem influence in crowdsourcing to be insignificant. The finding aligns with similar conclusions by Ye and Kankanhalli [21], suggesting that esteem or recognition holds limited motivational value in independent, task-oriented roles, as couriers' intentions to continue in last-mile delivery are not strongly influenced by the esteem or recognition they receive from peers or competitors [170]. This is in contradiction to other studies [12, 13, 15, 57, 58, 60, 69], which found a significant positive relation between Economic benefits and participating in crowdsourcing. One possible explanation for this finding is that couriers in crowdsourced delivery platforms, particularly in the Saudi market, operate independently with minimal interaction among peers. They perceive limited potential for gaining trustworthiness (EI1), recognition (EI2), respect (EI3), or reputation (EI4) through crowdsourced work. Couriers often see other couriers as competitors rather than sources of social support or recognition [171], which diminishes

the motivational role of esteem. Instead, couriers may prioritize personal efficiency and draw insights from others' successful practices without seeking external validation. This work environment's competitive and solitary nature emphasizes practical improvements and individual performance metrics, such as delivery times and customer ratings, over social recognition, making factors like trustworthiness, reputation, and peer recognition less relevant in influencing their continuous participation in crowdsourced delivery.

Regarding H2, the intention of the courier to stay involved in crowdsourcing was found not to be significantly influenced by the economic benefits (EB), matching with findings of a related study [172]. This indicates that rewarding incentives would not significantly affect continuing the courier service. However, our findings demonstrated that economic benefit has a statistically significant influence among male and committed couriers rather than occasional couriers. This suggests that monetary benefits in last-mile delivery may shift by demographics and levels of work commitment. One of the reasons could be that male couriers with those in committed roles may strongly esteem financial stability, choosing these jobs as a source of steady income or extra income. Their commitment is thus strongly based on economic incentives. On the other hand, female couriers might prioritize factors such as flexibility or security, which are not directly concerned with financial benefits. Correspondingly, couriers in occasional positions may view this job as temporary or secondary; thus, financial motivations will have less impact on their long-term contribution. For instance, students and part-time couriers make up a huge proportion of the workforce and more often value flexibility and enjoyment rather than finances [57]. These motivational differences also align with our findings, which show positive relationships between work autonomy, hedonic motivation, and effort expectancy with

continued participation behavioral intention. This would indicate that economic incentives, though reflecting couriers' preferences for flexibility and enjoyment rather than pure financial gain, may bear little influence on retention, at least at an irregular participation rate or when the couriers consider the courier role as a subsidiary source of income.

Hypothesis H3, Effort expectancy (EE), which refers to the perceived ease of using delivery systems and software, exhibited a path coefficient of 0.186 ($p < 0.05$), showing that an easier and more familiar system positively impacts courier intentions to remain in the delivery service. This finding is similar to of a related study Leung et al. [96], Liang et al. [69], and Zhang [60], It shows that there will be a positive relationship between effort expectancy and continued courier intention. Hedonic motivation (HM), hypothesis (H4), is the enjoyment couriers gain from their job and has a significant path coefficient of 0.314 ($p < 0.001$). This suggests that intrinsic joy and satisfaction are key couriers of their intents, which matches with the findings of related study Zhang [60], Huang et al. [173]. Hypothesis (H4) indicates a positive relationship between hedonic motivation and continued courier intention. Work autonomy (WA), hypothesis (H5), which reflects couriers' independence and control over their job, has a significant path coefficient of 0.284 ($p < 0.001$), demonstrating that autonomy significantly influences courier intentions to continue using the delivery service, similar to the findings of study Nguyen et al. [20], Ye and Kankanhalli [21]. Certainly, consistent with the fact that the freedom to select the distance and location of delivery is a strong motivator for couriers, particularly male, to increase their income by working more frequently. Delivery platforms must provide workers with more freedom by allowing flexible scheduling and encouraging them to take decisions, while also changing technology controls to increase performance. Eventually,

occasional couriers show a stronger effect due to work autonomy but are similarly affected by hedonic motivation compared to committed couriers. This implies that occasional couriers have the flexibility to choose their participation schedule, delivery location, and delivery distance.

In examining the sixth hypothesis (H6), which proposed that perceived concerns (a component of continued participation costs), such as payment delays or cancellations, health impacts, security risks, and restricted access to gated communities, might negatively influence couriers' intentions to continue working in crowdsourced last-mile delivery, our findings did not support this. This finding is consistent with other studies by Ye and Kankanhalli [21] and Huang et al. [59], which detected that some concerns might not significantly impact employees under specific conditions. Saudi Arabia's strict security laws and safe working environment guarantee that couriers don't have to worry about their health or safety, especially when they are working late or for extended periods of time. As well as successfully addressing payment concerns, this protected circumstance minimizes security and health concerns that would otherwise harm couriers in less regulated conditions [58]. Couriers are also more financially stable in areas with efficient payment legislation, reducing anxiety about the possibility of cancellation or delay in payments. The difference highlights the challenges in last-mile delivery across the globe. Unlike in other platforms with high COD practices that may result in delay or financial impasse, these markets offer a reliable payment method that in a way reduces the risk of financial loss [172]. Similarly, restricting entrance to gated or compound communities does not significantly lessen couriers' motivation to continue, as many regulated marketplaces have established procedures to allow entry. However, factors like safety, payment delays, and

access restrictions in areas with underdeveloped infrastructure and regulatory oversight may have a big influence on couriers' decisions to keep taking part. The significance of local legal frameworks in understanding how perceived risks impact courier retention in last-mile deliveries globally is shown by this disparity.

While this study is situated within Saudi Arabia, in which strong regulatory environments and trusted infrastructure diminish perceived concerns, these findings may well be very different in regions of less effective regulation or diminished economic confidence. These findings may indicate intrinsic motivators may have stronger logic in high-support regions, and extrinsic concerns, like safety and the reliability of payments, are likely to be more important in other areas. This requires further research to explore how different cultural and economic contexts might impact the generalizability of these findings across other markets.

6.2 Implications of the Research

This study investigated how benefit and cost variables affect courier's continued participation in crowdsourcing last-mile delivery, especially in urban areas, and provided strategies to improve couriers' participation and retention, coping essential factors for sustained involvement. Figure 1 depicts the research framework, utilizing the continued participation model (SET-UTAUT2) to analyze couriers' motivations. The findings imply that intrinsic factors like ease of use (Effort Expectancy), enjoyment (Hedonic Motivation), and independence (Work Autonomy) play a more crucial role in continuing courier participation than extrinsic factors, prestige (Esteem Influence), monetary rewards (Economic Benefit), and perceived price (Perceived Concern), especially within Saudi Arabia's delivery market as well as potentially in other regions with equal market dynamics

[21, 33, 58, 59, 174-176]. The theoretical and practical implications of the study are as follows:

6.2.1 Theoretical Implications

According to our knowledge, the empirical studies of factors impacting couriers' continued participation in crowdsourcing last-mile in emerging markets are limited, particularly under structured logistics sectors. Though financial rewards are a major motivation [58, 69] in participating of couriers, our findings indicate that intrinsic factors such as autonomy, easy working, and enjoyment may have a stronger impact on sustained participation than extrinsic benefits [12, 13]. Safe regions like Saudi Arabia, where security standards are high, payment systems are reliable, infrastructure is strong, and concerns and payment delays are low, these perceived costs tend to be insignificant compared to the intrinsic benefits of involvement. By integrating benefit and cost, this study develops an improved model that can explain the engagement of couriers in the logistics market environment. Our findings contribute to the literature on sustainable logistics by indicating that intrinsic benefits can play a significant role in sustaining participation in areas with sustainable infrastructure. These findings also have substantial implications for crowdsourced logistics platforms, underlining that human and network dynamics must be used to refine their processes. This might be useful insight into attracting and sustaining couriers in international markets as globalization advances, with the increasing ability of more regions, such as emerging markets, to develop structured logistics networks. The identified social and technological scope in crowdsourcing platforms are fundamental insights to support sustainable logistics operations [33, 177].

6.2.2 Managerial Implications

The improvement of courier satisfaction and retention in delivery platforms depends on job autonomy and flexibility to fit the needs of both occasional and committed couriers [172, 178]. Rewarding (Financial) benefits may appeal more to male committed couriers who value financial stability. Meanwhile, flexibility and security measures seem relevant to female couriers [57]. Platforms could profit from investing in technology like route optimization, real-time tracking systems, and transparent payment systems. These innovations will not only enhance efficiency by eliminating logistical difficulties but also increase the satisfaction of all involved workers by reducing their efforts in logistical challenges. Advanced secure digital payment strategies, such as e-wallets and QR codes, benefit businesses, enhancing financial security [174, 179]. Although mental and physical well-being were not the main drivers in this study, these remain valuable factors. Continuous training in customer service and vehicle handling can boost professionalism and help couriers tackle their own routes [34]. In a restricted area with limited entry availability, simplifying the delivery process can help ease concerns, especially when commercial banks provide payment upfront instead of delaying payment until delivery is received [58]. Fostering a supportive corporate culture that can address couriers' need for flexibility with secure, efficient work methods trades off flexibility against the longevity of work life.

To sum up, our findings demonstrate that effort expectancy, hedonic motivation, and work autonomy play pivotal roles in sustaining courier's involvement, particularly in Saudi Arabia. The flexible work decisions and supportive structures enhance commitment and adaptability for developing sustainable development goals (SDGs). The delivery platforms

best located to take advantage of this trend are those that are organized, make it easy for couriers to work a full day at tailored times, offer job-enriching facilities, and contribute to a resilient workforce adaptable to several regions in global markets. Ultimately, when the rules and work methods in crowdsourcing logistics are clear, understandable, and flexible, along with convenient and comprehensive enterprise training focusing on couriers' satisfaction, it leads to several benefits. It reduces costs, such as security issues, and eases stress that unforeseen situations could cause. It also helps them balance their personal requirements, such as family time. Supportive leadership can create a suitable work environment, especially when couriers are under stress, and their commitment to the work is acknowledged. This contributes to the possibility that employees will stay involved and continue with their roles.

6.3 Discussion of Request Acceptance Probability Model

The analysis of the M model's performance in predicting acceptances of delivery tasks from a dataset generated using valid questionnaires proved the above. Logistic regression was utilized to select the features to identify the most factors related to the study. It could identify the critical role of demographic and quantitative variables, such as gender, type of job, cost, distance, and delivery time, in influencing acceptance decisions.

Furthermore, all models were evaluated on some metrics, including accuracy, precision, recall, and F1-score.

For accuracy measurement, ANN, DT, SVM, XGBoost, GRU, AlexNet, and Soft Voting models achieved the highest accuracy of 91.06%. Random Forest (RF) and LSTM followed closely with 90.98% while LR scored the lowest at 89.05%. Regarding precision, LR outperformed other models with the highest precision of 91.54%. ANN, DT, SVM, XGBoost, AlexNet, and Soft Voting achieved 89.97%, while LSTM and GRU had slightly lower scores of 89.71%. For recall, XGBoost stood out with the highest score of 96.70%. RF, ANN, LSTM, GRU, and AlexNet followed at 93.09%. DT, SVM, and Soft Voting were close behind with 92.94%, while the lowest LR lagged significantly at 86.66%. Lastly, for the F1-score, ANN achieved the highest at 91.46%, closely followed by DT, SVM, XGBoost, AlexNet, Soft Voting 91.43%. RF, LSTM, GRU 91.37% performed slightly below 91.37%, with LR again showing the lowest performance at 89.03%.

Among all the tested models, ANN and XGBoost demonstrated superior performance across multiple metrics, including accuracy (91.06%) and F1-Score(91.46% for ANN, 91.43% for XGBoost). Both models also maintained high precision at 89.97%, while for recall, XGBoost achieved the highest scores of 96.7% and ANN closely with 93.09%, supported by their advanced computational ability to handle complex patterns within large datasets.

Other models such as DT, SVM, AlexNet, Soft Voting, GRU, RF and LSTM also performed robustly, indicating their robustness in classification tasks even within the varied and unpredictable logistical environments. Their high metrics scores show evidence that these models will be effective, which is crucial in ensuring the reliability of delivery task predictions.

In contrast, the performance of the LR model was the weakest, with far lower scores in all metrics, which could be a consequence of the very simplistic assumption in the feature independence that could easily be violated in complex real-life datasets. This limitation is essential in logistics, because compensation, distance, and delivery time are all interdependent and have a considerable impact on decision-making.

The assessment of sensitivity analysis affirmed that compensation, distance, and delivery time play a crucial role in determining task acceptance. Shorter delivery times and higher compensation were positively correlated with higher acceptance rates, while longer times and lower compensation led to increased rejection rates across distances of 15-25 km. In contrast, distance had a lesser effect on the acceptance decision, indicating that time efficiency and financial incentives were more significant factors in couriers' decision-making processes. These insights suggest that couriers prioritize task efficiency and compensation when making decisions, offering valuable insights for optimizing tasks assignments in crowdsourced delivery systems. Further evaluation of the models used for predicting delivery tasks acceptance established that the best performing models were Random Forest (RF), XGBoost, and Soft Voting. Among various metrics such as accuracy, precision, recall and F1-score, Random Forests demonstrated superior performance, achieving accuracy (95.60%), precision (95.79%), recall (95.46%), and F1-score (95.63%). XGBoost followed closely, outstripping in recall (96.35%) and consistently providing reliable identification of positive outcomes. Ensemble methods like Soft Voting also showed strong results, with an accuracy of 94.84% and F1-score of 94.89%. Regarding deep learning performance, GRU, ANN, and LSTM yielded strong results followed by DT. AlexNet and SVM also delivered competitive results, while LR did not show such

remarkable performance across several measures, including recall, highlighting its limitations in capturing complex relationships within data.

This study has used predictive modeling to establish a strong ground on how one can enhance predictive modeling in logistic functions, especially in the automation and optimization of delivery task assignments. The current study demonstrated outstanding performances from the ensemble models (XGBoost, RF, Soft Voting), followed closely by strong results from deep learning models (ANN, GRU, LSTM, and AlexNet), and solid performance from classic machine learning models (DT, SVM, and LR) indicate their potential applicability in the development of real-time predictive systems that will dynamically adapt to changing conditions in a logistics landscape. This study also seems to confirm the importance of features such as feature selection and model tuning in the quest for higher prediction accuracy.

In summary, this validates the strength of highly ML techniques in logistical applications and shows areas for improvement, especially concerning the sensitivity of models towards feature interdependence. These insights contribute to the comprehensive understanding of predictive modeling for courier behavior in crowdsourced delivery systems and provide actionable recommendations for future research and practical implementation.

CHAPTER 7

CONCLUSION, LIMITATIONS, AND FUTURE WORK

7.1 Conclusion

The sustained involvement of couriers is critical for the advancement of last-mile delivery firms. This study makes use of (SETM) and (UTAUT2) to investigate both the benefits and the costs that affect the decision to keep working as a courier. Based on this analysis, suggestions are made to companies on how to strategically plan courier tasks so that individuals are motivated to give their best efforts more efficiently. This goal can be accomplished through a variety of strategies. Organizations may, for instance, place a higher priority on improving the qualities and attributes of couriers by assigning work that best suits their skill sets, allowing them more autonomy in their work, and helping them establish a positive esteem, economics, effort, enjoyment, and lower perceived risks from the job. The research finds that factors like effort expectancy, hedonic motivation, and work autonomy significantly impact couriers' sustained participation, whereas variables such as esteem influence, economic benefit, and perceived concern have no significant impact. Additionally, the study revealed that differences in motivation between occasional and committed couriers affect their intentions to stay in their jobs, with economic benefits positively impacting male and committed drivers' intentions to continue working. It is important to consider intrinsic and extrinsic factors, provide a professional, and supportive environment to promote driver engagement in crowdsourced last-mile delivery.

The study has addressed common method bias, multicollinearity, and autocorrelation, proving they were not a problem to ensure the reliability of the results. Furthermore, the endogeneity tests revealed no bias, further reinforcing the robustness of the findings.

The second part of the research focused on predicting task acceptance by using ML techniques. For analysis of the original data, the most robust model is ANN and XGBoost, as they depict a strong performance regarding all the metrics presented; thus, they would be perfect for future research on prediction, optimization, and scheduling tasks. Furthermore, Soft Voting, AlexNet, GRU, DT, and SVM achieved strong results, especially in scenarios requiring balanced metrics. Random Forest (RF) and LSTM highlighted as adequate predictive models for applications requiring high recall and sensitivity, while LR excelled in precision. These results show the effectiveness of advanced machine and deep learning models for improving task acceptance rates and decision-making in last-mile delivery logistics.

The sensitivity analysis further reinforced the importance of delivery time, compensation, and distance in influencing task acceptance. Higher compensation and shorter delivery times were associated with higher acceptance rates. Likewise, longer delivery times and lower compensation also resulted in higher rejection rates. Although distance had a relatively smaller effect compared to time and reward, it remained a significant factor, indicating that couriers' priorities time and compensation over distance when choosing tasks. These findings also contribute to the power of ensemble learning models (RF, XGBoost, and Soft Voting), in optimizing the prediction of task acceptances.

In conclusion, this study demonstrates that predictive modeling can significantly improve logistics by automating delivery task assignments. Ensemble models (XGBoost, RF, and

Soft Voting) performed exceptionally well, as well as strong results of deep learning models (ANN, GRU, LSTM, and AlexNet) and then classic machine learning models (DT, SVM, and LR), thus confirming their usefulness in the creation of predictive systems that operate in real-time. Such systems are intended to optimize according to the specified time-variant logistic requirements, thereby enhancing the efficiency and effectiveness of last-mile logistics. The research highlights the importance of feature selection and model tuning to achieve a satisfactory prediction performance and better last-mile delivery logistics.

7.2 Limitations and Future work

The study offers valuable perspectives on the scope of continuous courier engagement acceptability in Saudi Arabia's crowdsourcing last-mile delivery services. It is important to consider its limits. For the first study, the survey sample primarily includes participants from urban areas, which raises the possibility of variations in service, environmental conditions, and other elements compared to rural locations. Secondly, most female participants are newly working in this business and lacked full knowledge and understanding of this emerging technology, affecting some factors in the study results and making them insignificant. Thus, additional research is warranted to explore other facets of couriers' involvement in last-mile delivery to promote the sustainable expansion of the industry. Furthermore, the study focuses on last-mile delivery services. Still, it does not address the broader array of goods such as food, beverages, parcels, clothing, cosmetics, each of which possesses distinct characteristics. Future research should focus on examining specific services, rather than generalizing, to facilitate a deeper understanding of the study and easier analysis of its results.

Additionally, this study reflects certain biases and demographic imbalances within its sample that may influence the findings. The sample includes a high proportion of students (55%) whose motivations may differ from those of full-time couriers, potentially impacting the findings. Furthermore, the male representation at 74% introduces gender bias, limiting the generalizability of the findings to a more diverse courier population. More balanced and diverse samples in future studies would improve the applicability and robustness of the study's insights, contributing to a comprehensive understanding of continuous courier engagement in crowdsourced last-mile delivery.

For the second study, while demonstrating the effectiveness of ML models for task acceptance prediction, limitations include the dataset only covered Saudi Arabia, which may not be applicable in other regions with different culture, economy, or logistical contexts. Moreover, the limited sample size restricts the robustness of the results. Extending the dataset by adding various geographical areas and demographics may positively affect the generalizability of predictive models and deeper insights into global courier decision-making. Furthermore, although advanced machine and deep learning algorithms were used in this study, investigating other algorithms and incorporating additional features, such as seasonal variations and weather conditions, would improve models' performance. Future studies should also apply real-time system tracking data and recurrent reinforcement learning to enhance flexibility over time. Moreover, hybrid models that employ different techniques could further optimize task acceptance prediction and improve operational effectiveness in last-mile delivery.

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Islamic Alkuraimi Bank, Taiz (Jan 2018 – Jan 2020)

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Suzuki Egypt Company for Cars, 6th of October City, Egypt (Oct 2014 – Dec 2014)

- *Industrial & Manufacturing Systems Application:* Applied production and quality-control methods, enforced safety protocols, and gained hands-on experience in welding, painting, assembly, and maintenance.

Misr University for Science & Technology (MUST), 6th of October City, Egypt (Oct 2014 – Dec 2014)

- *Industrial & Manufacturing Systems Application:* Optimized production processes, implemented facility management strategies, and leveraged engineering technology to enhance operational efficiency.

Mansoura University, Faculty of Engineering, Al Mansoura, Egypt (Aug 2014 – Dec 2014)

- Gained hands-on experience in electrical and control systems, implemented renewable energy solutions, integrated robotics and AI, and developed proficiency in industrial instrumentation and control.

Yemen Company for Ghee & Soap Industry, The Mukha Power Station, and Yemen Cement for Industry & Marketing, Taiz (Jan 2013 – Jul 2014)

- Acquired familiarity with key production and service facility sections, including product design, production processes, planning, operations management, product management, R&D, safety & security, quality control, and maintenance.

Publications

Journal Papers

- **M Alromema**, A Al Hanbali, A Baubaid, A Al Ghazi, NT Khan, and Z Saleh. “Factors Influencing Couriers’ Acceptance of Crowdsourcing Last-Mile Delivery in Saudi Arabia.” *International Journal of Logistics Management (IJLM)*, November 19, 2024. Under Review
- **M Alromema**, MA Makarem. “Enhancing Evolutionary Solver Efficiency for NP Hard Single Machine Scheduling Problems.” *International Journal of Science and Research (IJSR)*, December 1, 2023.

Conference Papers

- **M Alromema**, Z Saleh, and MM Aldurgam. “Comparative Analysis of a VMI System in a Two-Echelon SC Versus Traditional Systems with Flexible Production Rates.” *SMILE Conference, KFUPM, Saudi Arabia*, September 17, 2024.
- Z Saleh, A Baubaid, A Al Hanbali, and **M Alromema**. “Comparing Reinforcement Learning Algorithms for Online Couriers Scheduling in Crowdsourced Last-Mile Delivery.” *SMILE Conference, KFUPM, Saudi Arabia*, September 19, 2024.
- AA Sleem, **M Alromema**, and MAM Abdel-Aal. “Improved Bass Model by Using Sales Proportional Average for One Condition of Mono Peak Curves.” *CIE50 Conference, Sharjah, UAE*, October 30, 2023.

Appendices

Appendix I

Appendix I: Survey Design

Survey on Acceptance Factors Influencing the Individuals' Continued Participation as Couriers in Saudi Arabia

Dear participant,

I sincerely appreciate your participation in my thesis for the master's program (Industrial Systems Engineering) at King Fahd University of Petroleum and Minerals. This survey aims to explore acceptance factors influencing the continued participation of individuals as Couriers in crowdsourcing logistics, which involves the utilization of independent couriers to deliver goods from various sources to their final destinations. Your feedback will greatly contribute to our understanding of this topic. The survey will take about 4 to 5 minutes to complete.

Best regards

Mohammed Alromema

Master student in KFUPM

After you complete the survey, if you want to participate in the lottery, **please enter any information (e.g., email, or phone number, any information)** that ensures your participation to win the prize. The prize will be **500 SAR** shared between the first and second places. The lottery will be held after reaching the required number for the study. Please note that this information will be used for lottery purposes and your information will remain confidential and private. Good luck!

Survey: -

Before answering the following questions, please read the question below carefully:

A. What is your gender?

☐ Male ☐ Female

B. Which age group do you belong to?

☐ 18- 25years ☐ 26- 35years ☐ > 35 years

C. What is your occupation?

☐ Student ☐ Employed ☐ Self-employed ☐ Other

D. How much is your income/month?

☐ Less than 2000 SAR ☐ 2000-5000 SAR ☐ More than 5000 SAR

E. What type of delivery task would you prefer?

☐ Occasional (available for uncertain period, pay per order) ☐ Committed (available for a certain period, pay per order and hourly pay) ☐ None

F. What is maximum distance willing to deliver?

☐ Short (5- 15 km) ☐ Moderate (16-25 km) ☐ Long (26- 35 km)

G. What is maximum trip time (your location, pickup and delivery time) willing to deliver?

☐ Short (5-20 min) ☐ Moderate (21-40 min) ☐ Long (41-60 min)

H. Would you be willing to continue accepting delivery tasks in crowdsourcing logistics?

☐ Yes ☐ No

I. Scenario:

Imagine You're participating a crowdsourcing delivery platform, and it presents a specific delivery task along your route (e.g., free time, going to work, or a specific task). Please choose the preferred option for each question, **indicating the maximum time you're willing to trip for compensation and the distance of the delivery task.**

Q1. For (20 SAR with 15km) What is the maximum time you are willing to deliver?	Q2. For (20 SAR with 25km) What is the maximum time you are willing to deliver?	Q3. For (30 SAR with 15km) What is the maximum time you are willing to deliver?	Q4. For (30 SAR with 25km) What is the maximum time you are willing to deliver?	Q5. For (40 SAR with 15km) What is the maximum time you are willing to deliver?	Q6. For (40 SAR with 25km) What is the maximum time you are willing to deliver?
a. 20 min ☐	a. 20 min ☐	a. 20 min ☐	a. 20 min ☐	a. 20 min ☐	a. 20 min ☐
b. 40 min ☐	b. 40 min ☐	b. 40 min ☐	b. 40 min ☐	b. 40 min ☐	b. 40 min ☐
c. 60 min ☐	c. 60 min ☐	c. 60 min ☐	c. 60 min ☐	c. 60 min ☐	c. 60 min ☐
d. unwilling ☐	d. unwilling ☐	d. unwilling ☐	d. unwilling ☐	d. unwilling ☐	d. unwilling ☐

Strongly disagree Disagree Neutral Agree Strongly agree

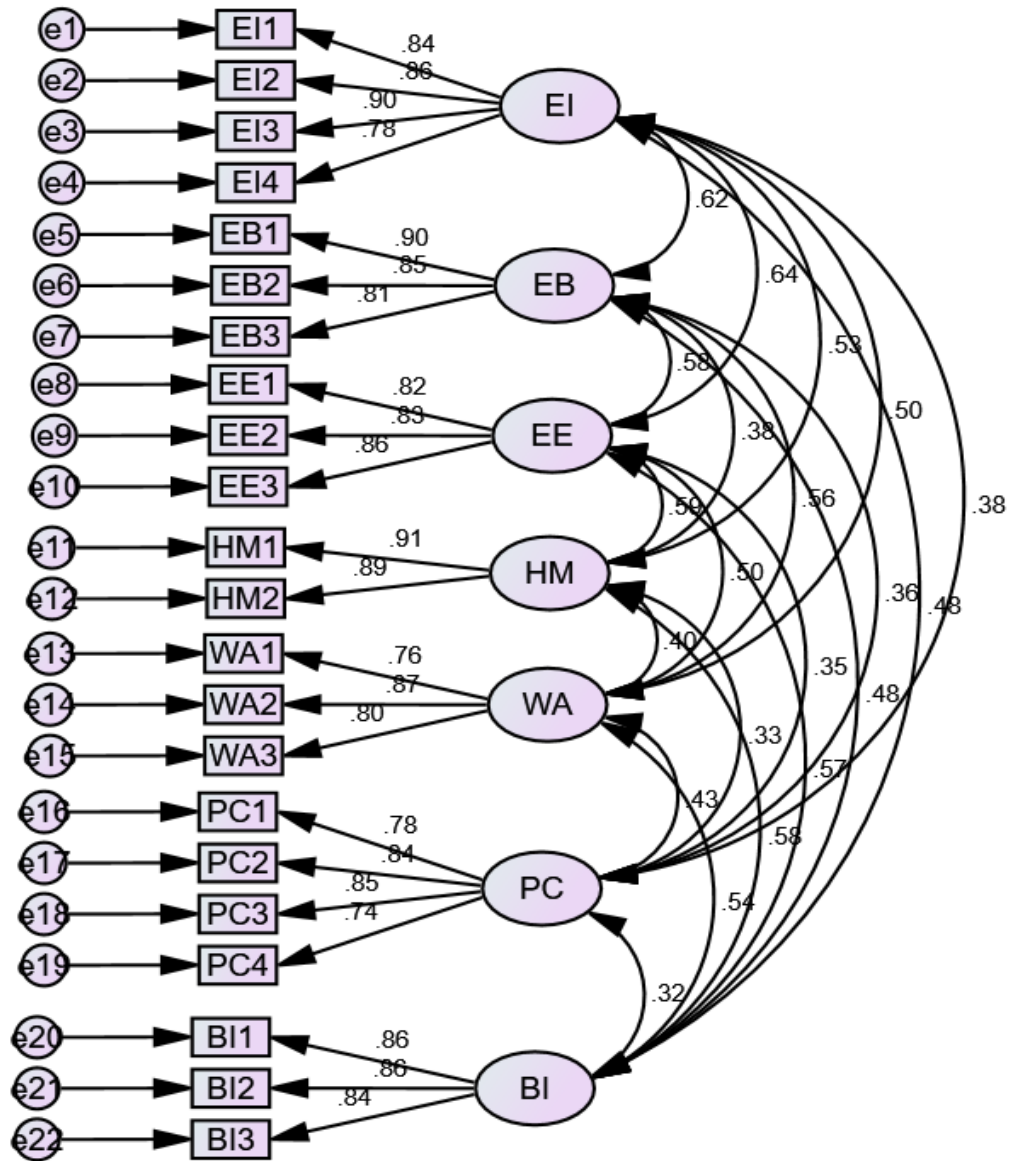
1. As a courier in crowdsourcing logistics, I earn trustworthiness.	☐	☐	☐	☐	☐
2. As a courier in crowdsourcing logistics, I earn recognition.	☐	☐	☐	☐	☐
3. As a courier in crowdsourcing logistics, I earn respect from others.	☐	☐	☐	☐	☐
4. As a courier in crowdsourcing logistics, I earn a better image within the community.	☐	☐	☐	☐	☐
5. Working as a courier benefits me financially.	☐	☐	☐	☐	☐
6. My monthly income increases when I work in crowdsourcing logistics.	☐	☐	☐	☐	☐
7. The primary reason to become a courier is earning money.	☐	☐	☐	☐	☐
8. It is easy for me to work in the crowdsourcing logistics skillfully.	☐	☐	☐	☐	☐
9. The rules and work methods in the crowdsourcing logistics are clear and understandable.	☐	☐	☐	☐	☐
10. Crowdsourcing logistics delivery is convenient. (such as easy to pick up and delivery, etc.).	☐	☐	☐	☐	☐
11. Participating in the crowdsourcing logistics is fun.	☐	☐	☐	☐	☐
12. Participating in the crowdsourcing logistics is entertaining.	☐	☐	☐	☐	☐
13. I have options to select my Participating schedule.	☐	☐	☐	☐	☐
14. I have options to select my delivery location.	☐	☐	☐	☐	☐
15. I have options to select my delivery distance.	☐	☐	☐	☐	☐
16. I am concerned about payment delay or cancellation from customer.	☐	☐	☐	☐	☐
17. I am concerned about the impact of Participation on my health.	☐	☐	☐	☐	☐
18. I am concerned about the impact of participating on my security.	☐	☐	☐	☐	☐
19. I am concerned that Restricted access in gated (compound) community affects my participation.	☐	☐	☐	☐	☐
20. I will continue to participate in crowdsourcing logistics in the future.	☐	☐	☐	☐	☐
21. I will frequently Participate in the crowdsourcing logistics when available.	☐	☐	☐	☐	☐
22. I am willing to recommend crowdsourcing logistics to my friends and family for participation.	☐	☐	☐	☐	☐

If you would like, please share any information that ensures your participation in the lottery for a chance to win the prize (e.g., email, or phone number, any information).

(.....)

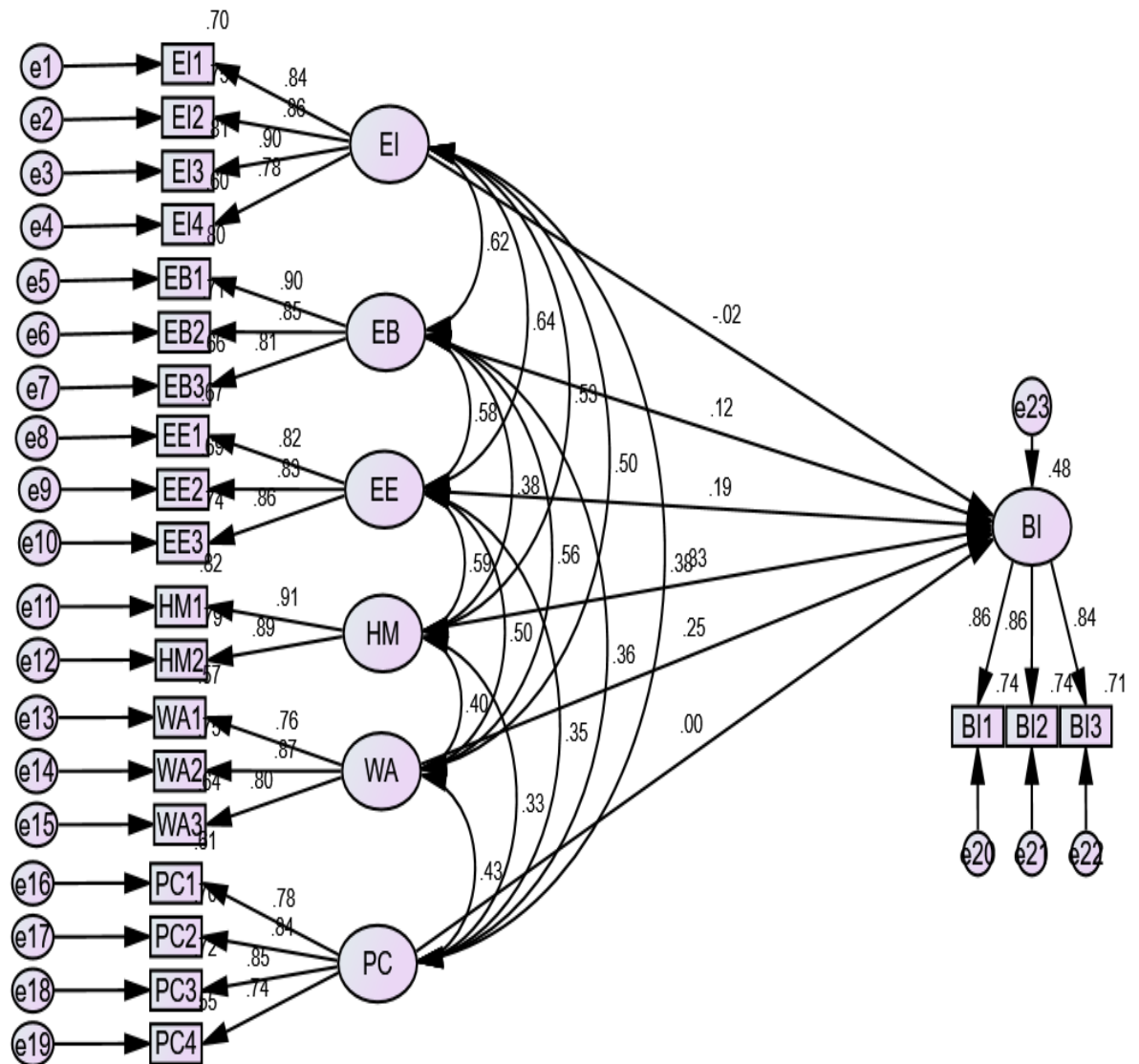
Appendix II

Appendix II: Final measurement model



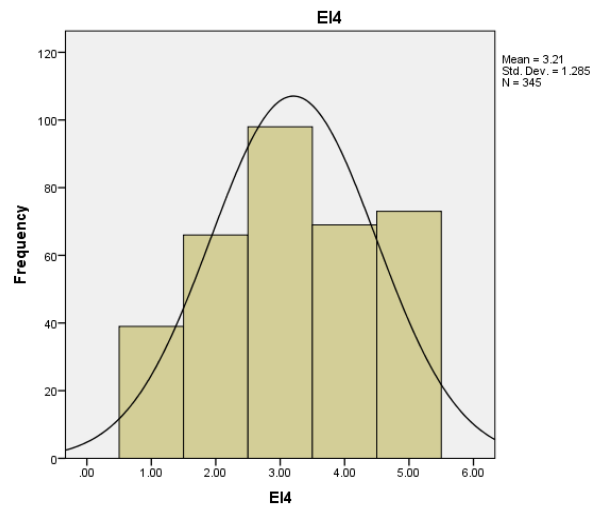
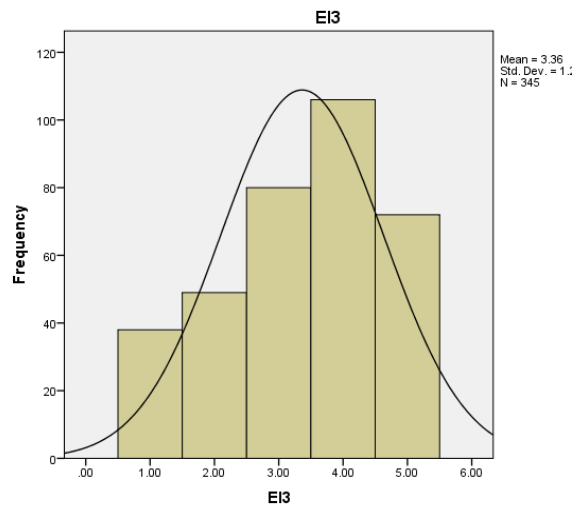
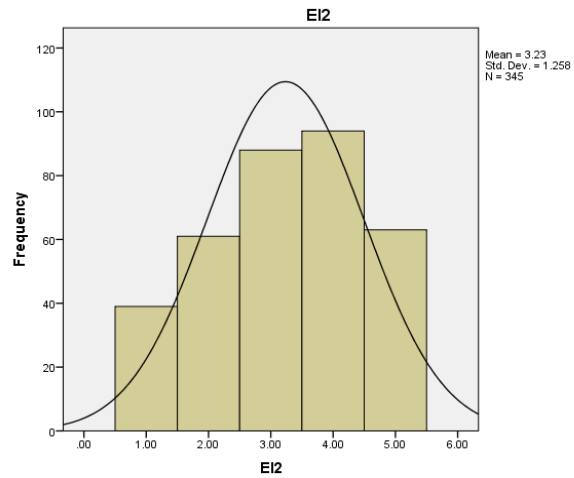
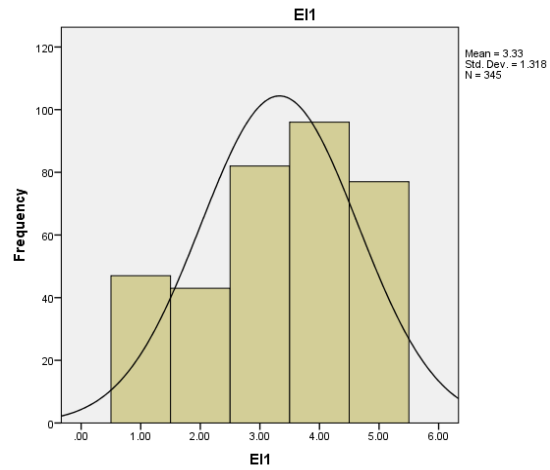
Appendix III

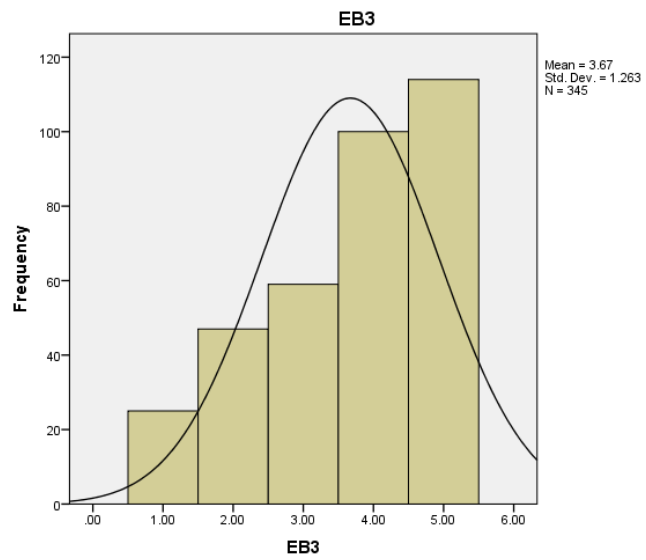
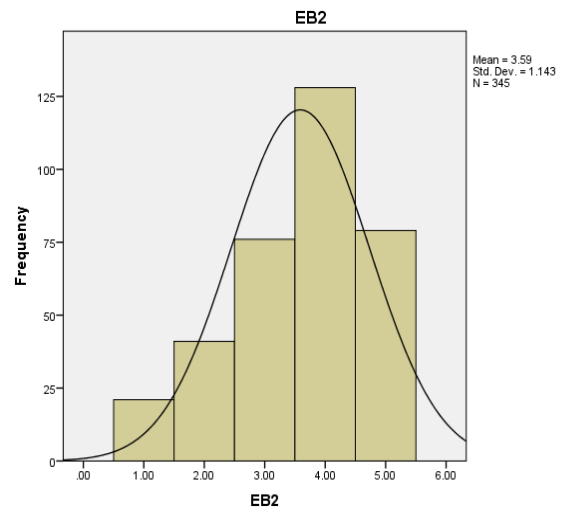
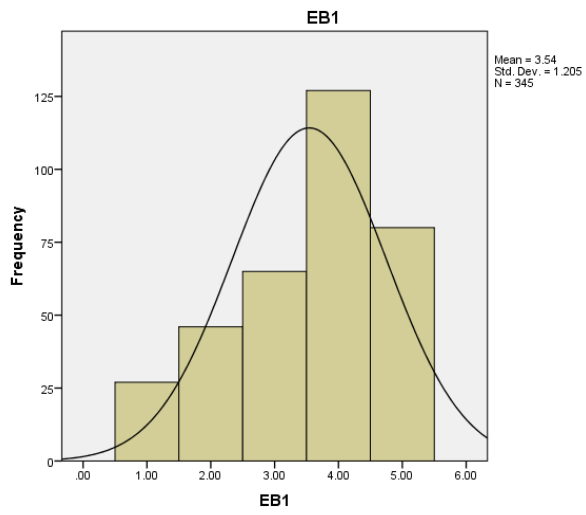
Appendix III: Final structural model

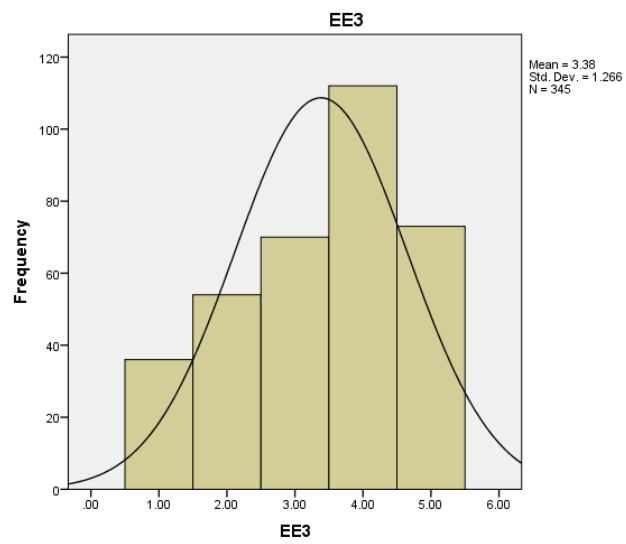
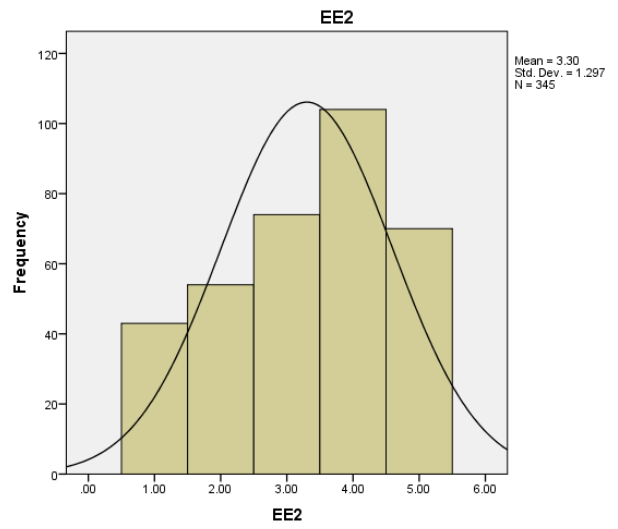
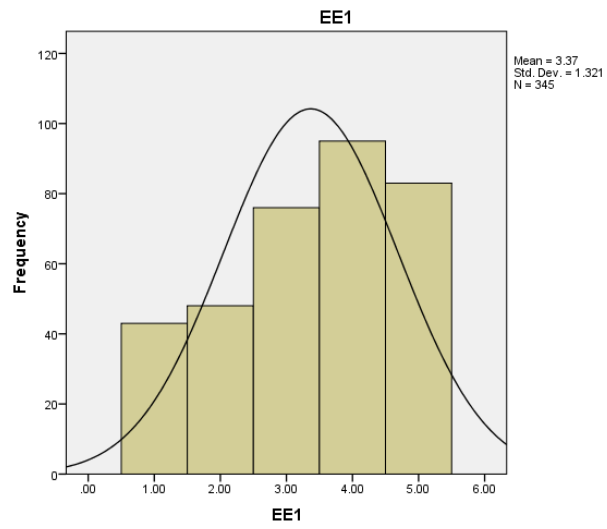


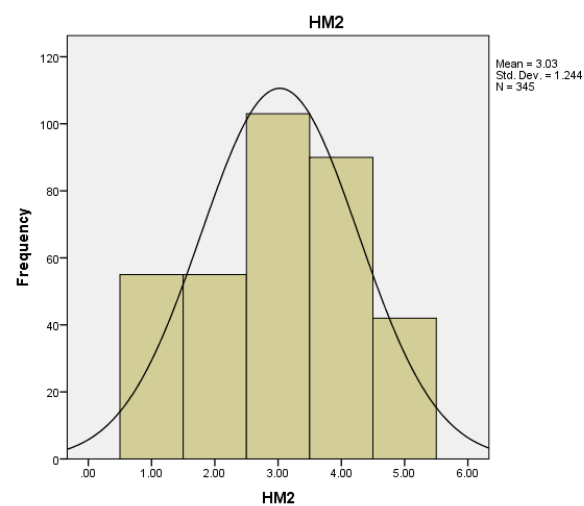
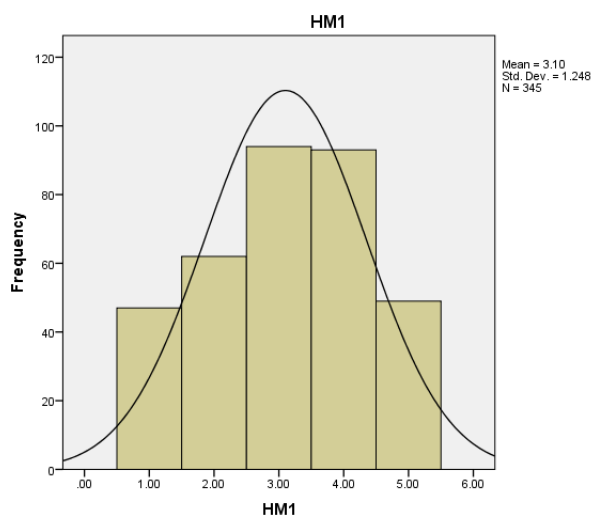
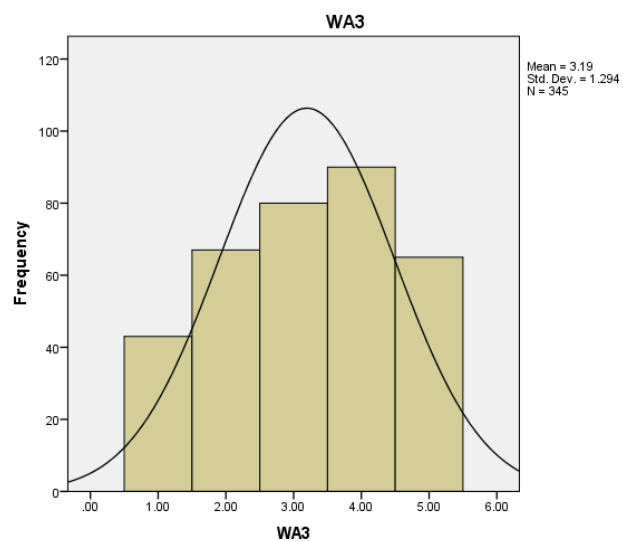
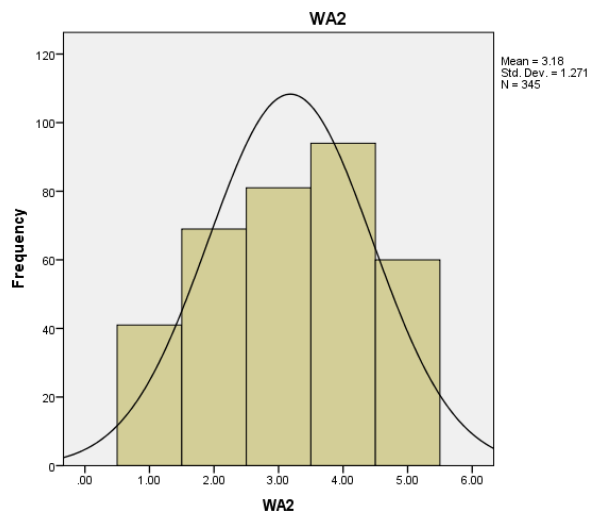
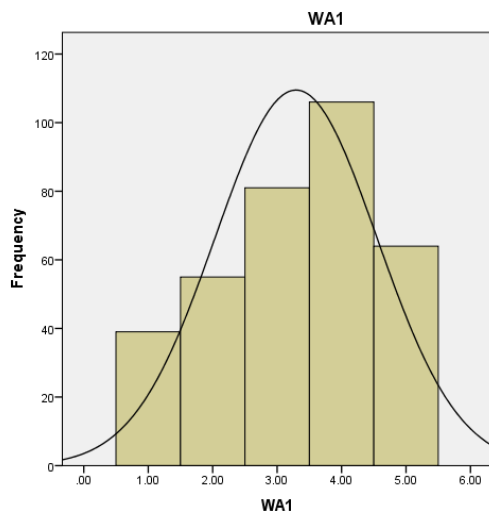
Appendix IV

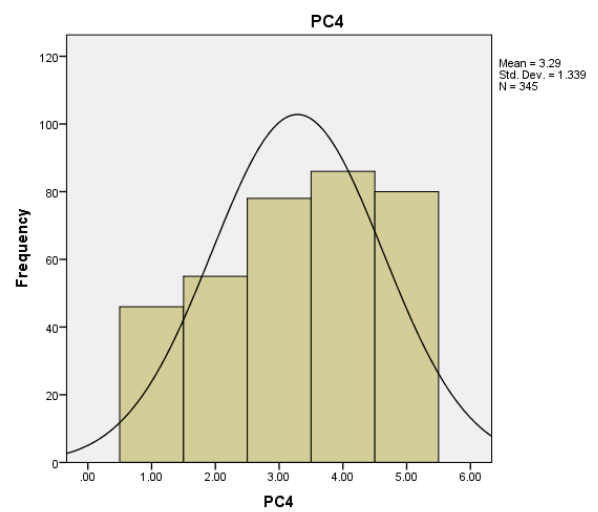
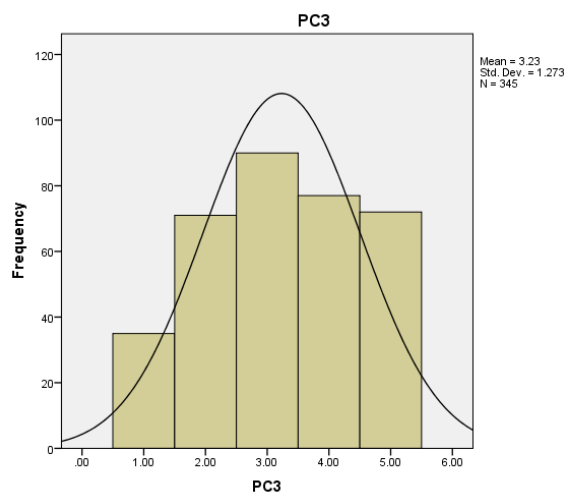
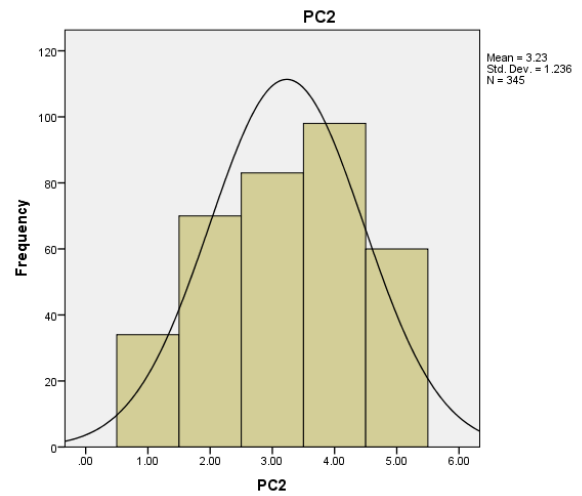
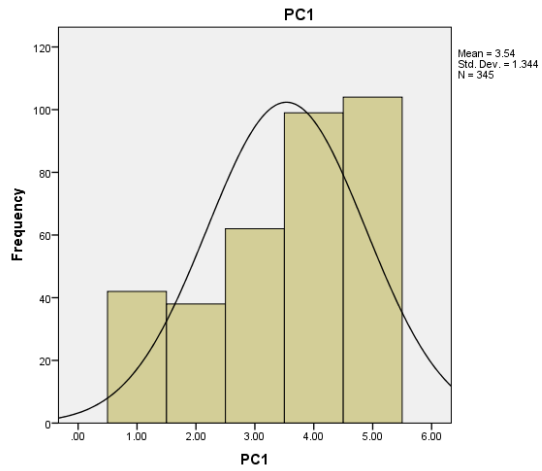
Appendix IV: Frequency Distribution Histograms of factors influencing continuous couriers' intentions in crowdsourced delivery

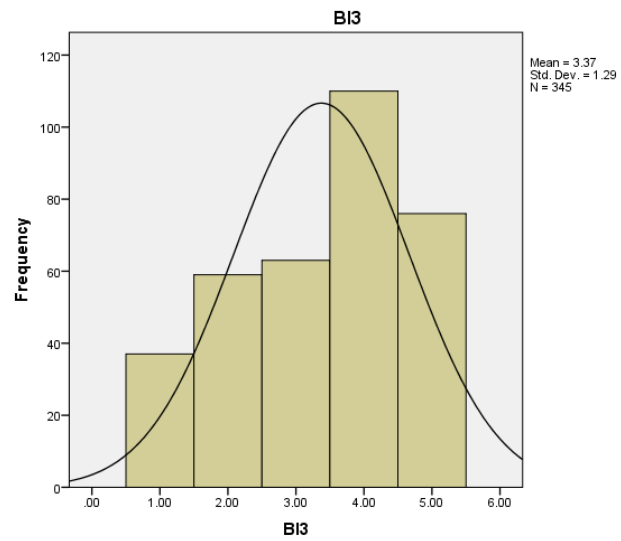
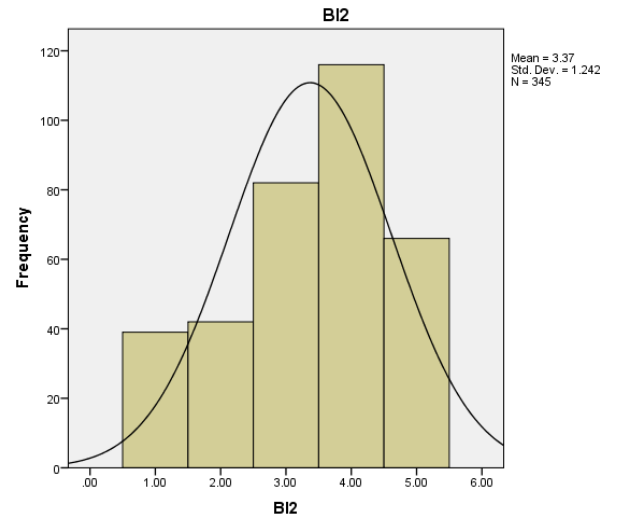
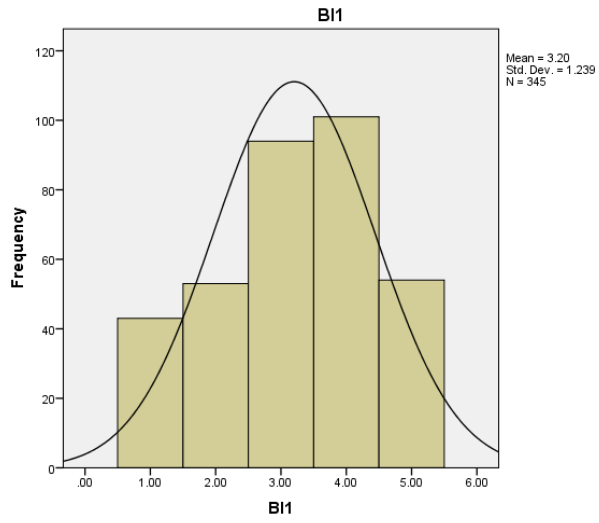












Appendix V

Appendix V: Correlation Matrix

