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Unlocking Hidden Demand: Utilizing Computer Vision for Street-Hailing Optimization in a Taxi Company in Jakarta

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ABSTRACT: Despite the technology disruption from online ride-hailing, street-hailing is still popular among certain people in Jakarta, the capital city of Indonesia. However, the traditional street-hailing faces several challenges for the taxi operators. Unlike ride-hailing apps where customers and drivers are matched and recorded digitally, street-hailing often lack visibility into street demand that is not always successfully picked up, which can lead to inefficiencies in fleet utilization, highlighting a significant operational gap between traditional taxi services and modern ride-hailing platforms.
Artificial Intelligence (AI) and Computer vision (CV) technologies offer a transformational approach to improve visibility and identify the unmet demand for street-hailing within urban transportation in Jakarta. Prior to its implementation, it is important to assess the potential business impact from deploying this digital innovation. This research highlights inference statistics combined with qualitative analysis to evaluate the potential demand that can be captured through CV systems. By leveraging historical taxi trajectory data and interviewing drivers and customers, we aim to uncover patterns and estimate unmet demand to ensure the system development will impact the taxi business and improve the service efficiency and customer satisfaction. This preliminary analysis serves as a foundation for strategic planning of CV system for street-hailing detection implementation.

KEYWORDS: taxi; street-hailing; unmet demand; computer vision; artificial intelligence; digital innovation; business impact

I. INTRODUCTION

For many years, taxis have played an important role in urban transportation in almost all big cities in the world, providing convenient and efficient point-to-point travel options [1–3]. In the past, when someone wanted to get a taxi ride, they would simply step out onto the street and raise a hand to hail one. This gesture has become widely recognisable and understandable among both drivers and the customers. It has become a symbol of a social interaction between taxi drivers and hailers in many major cities around the world [4, 5].

However, with the emerging of modern technology, many industries have undergone a significant transformation, and this hand signal to hail a taxi is no exception. As the digital era introduced innovative platforms, ride-haling applications like Uber shifted the way people hailing a taxi [6, 7, 7]. These platforms, built on sophisticated technology, were designed to connect drivers directly to passengers to provide taxi trips [1–3, 8, 9]. They managed to do this with such efficiency that the entire experience become streamlined and much more appealing to users. This newfound efficiency posed a considerable challenge to traditional taxi services. The ease of booking, predictability of service, and transparent pricing systems of these apps began to overshadow the older taxi-hailing model.

Despite this modern advancement, the old practice of flagging down a taxi on the street remains popular, particularly in some areas and among certain groups of people [5, 10]. The quick and easy experience of raising an arm and catching a taxi on-the-fly has a sense of immediacy and convenience that apps cannot replicate. This often caters to spontaneous decisions, whereas app-based services require a bit pre-arrangement.

Leading taxi companies in South-East Asia have recognized the continuing popularity of street-hailing and adapted their services to cater to this demand. ComfortDelGro (CDG) in Singapore reports that a significant majority, about 60% of its passengers still hail taxis from the street. To cater to this substantial customer base, CDG has introduced features like “Pay for Street Hail” option in their app, enabling cashless payments for street-hail rides [11]. Similarly, Blue Bird Group in Indonesia highlights in their annual report the importance of street-hailing in their multi-channel strategy by implementing features like EZPay to facilitate cashless transactions for street-hailing rides, recognizing the need to enhance the customer experience for this traditional hailing

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method [12]. These examples suggest that street-hailing, far from being obsolete, continues to play a vital role in the taxi industry and remains a preferred options for many passengers.

From a business perspective, traditional street hailing poses several challenges for taxi operators. One of the major concerns is the missed opportunity to generate revenue. Drivers might not be able to see passengers who are looking for a ride, especially in crowded or visually obstructed areas due to the high density of vehicles and pedestrians (see Figure 1). Drivers' attention when driving might be split between multiple tasks such as monitoring traffic signals, navigating, and watching for other road users, that can lead to missed hailing opportunities. Drivers might be flagged down by individuals on the street when the taxis are already occupied, as visualized in Figure 2. They also might already be dispatched by a dispatching system, driving on their way to pick up another customer, as their priority is to reach the confirmed customer in a timely manner. These situations can lead to missed hailing opportunities, frustration for passengers trying to get a ride, and a decrease in efficiency for the taxi service which translates directly in lost earnings, with taxis around empty, while the potential passengers are nearby.

Figure 1. Scenario where a taxi driver in a crowded road fails to notice a customer attempting to hail the taxi.

Figure 2. Scenario when a customer is hailing a taxi on a sidewalk when it is occupied.

Unlike app-based orders, traditional street hailing is not recorded digitally by the system, meaning that the company does not have a complete picture of demand in each area, which is often assumed to be small. No data is recorded when the passengers begin to wait for hailing a taxi [8]. As a result, it is difficult to determine the actual supply in each area. It can lead to either oversupply areas where demand is perceived to be high based on app data or undersupply areas where street hailing is common but unrecorded. As illustrated in Figure 3, since there is no available taxi in the area where the customer is waiting, the customer might finally decide to leave or opt for another transportation mode, which means the loss of opportunity for the taxi operator.,

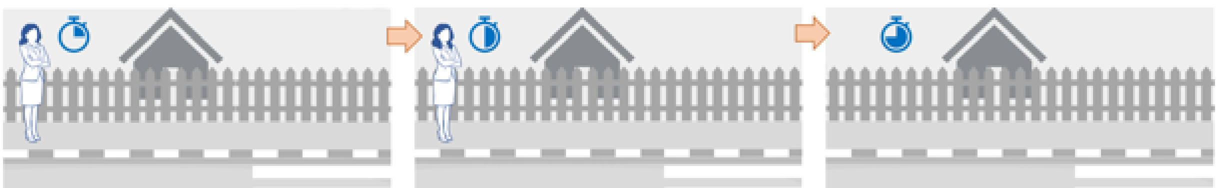

Figure 3. Scenario when a customer is waiting for a taxi until she is leaving out.

Safety is also another critical concern in street hailing. The act of waving down a taxi can startle drivers, potentially causing accidents or sudden brakes that could trigger a chain reaction in heavy traffic. Furthermore, a taxi slowing down or stopping harshly to pick up passengers might not be anticipated by other drivers on the road, causing the risk of rear-end collisions. The conditions are even worse during night-time. Dim lighting and reduced visibility can make it difficult for drivers to spot and safely approach potential passengers.

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There is an undeniable emphasis on customer experience. In a world where user experience drives loyalty, potential passengers who consistently fail to hail taxis, especially during peak time or challenging conditions, might abandon traditional taxis altogether. Therefore, finding a solution that ensures taxis can efficiently detect and respond to street hails is not just a matter of revenue, but also long-term viability in an ever-evolving transportation landscape.

To address these challenges, there is an evident need for technological intervention, and this is where the camera technology presents a promising solution. Taxis equipped with advanced camera systems placed in the right position with a wide enough field of view capture the road ahead and the sidewalk in front. The camera is then integrated with the Internet of Things (IoT) system with the Computer Vision (CV) and Artificial Intelligence (AI) applied to send and process the image data in real-time. To validate the feasibility and potential effectiveness of this approach, a focused research investigation is required. The following research questions will guide this inquiry, aiming to provide actionable insights for the implementation:

- **RQ1:** What is the business impact of utilizing computer vision for street-hailing detection if implemented in Jakarta?
- **RQ2:** How can the CV technology be effectively implemented to detect potential street-hailing demand?

By addressing these questions through research, this study seeks to establish a firm foundation for the implementation of the AI and computer vision to unlock hidden demand of taxi street hailing, ultimately contributing to the resolution of the overarching business issues.

II. LITERATURE REVIEW

AI and CV technology is evolving rapidly and has reshaped the business landscape. Unexceptionally in the transportation industry, the CV has brought significant advancements for at least improving operational efficiency, enhancing transportation safety of road users, increasing productivity for the industry players, and analyzing traffic condition for any purpose [13]. Particularly for this research, the rapid advancement of CV technology has opened an idea for leveraging the technology to improve the visibility of unmet demand in the taxi industry. However, before implementing such technologies, it is crucial to understand the potential impact on the business. This requires a thorough examination of existing research on CV for detection street hailing and inference methods for estimating demand. This literature review aims to provide overview of existing research on CV for street-hailing detection and inference methods for demand estimation. By synthesizing the current state of knowledge, this review will inform the development and implementation of AI-powered solutions to improve the efficiency and accessibility of street-hailing services while mitigating potential risks and ensuring a positive impact on both business and society.

A. Computer Vision for Street Hailing Detection

CV is fundamental to the development of taxi street-hailing detection. A study developed by Mastouri et al. (2023) in their research titled "A Context-Aware, Computer-Vision-Based Approach for the Detection of Taxi Street Hailing Scenes from Video Streams" suggests the implementation of such technology. Individuals who is standing on a sidewalk or close to the road and making a hailing gesture is captured by a dash-cam, then the image is transferred to an AI system and automatically recognized as a demand [5]. The study does not only propose the visual integration, but also uses contextual information, such as time of day, location, and weather conditions to improve the accuracy of street hailing detections. The contextual information allows for a more nuanced understanding of demand patterns, capable of identifying not only waving-hand gesture but also implicitly revealing variations of hailing behaviors by only standing by the sidewalk in an unmet demand across different situations.

The paper contributes to the literature by demonstrating the feasibility and potential impact of CV technology in addressing unmet demand in the taxi industry. Implementing the CV for street hailing detection improves the visibility of unmet demand. The unlocked hidden demand data captured from street hailing detection system can be stored in a storage system for future analysis.

B. Inferring Unmet Demand

As the street-hailing interactions are typically not recorded by the systems until a passenger is onboard, identifying and quantifying unmet street-hailing demand has posed a huge challenge for a taxi industry [2, 14]. This condition may cause the operational inefficiency to match taxi supply with the demand, and potentially results in revenue loss. However Afian et al. (2015) in their research titled "Inferring Unmet Demand from Taxi Probe Data" have proposed a framework to address this issue. This study suggests an innovative method for estimating potential taxi demand by utilizing taxi trajectory data, which includes information about taxi trips, including timestamps, and routes taken during vacant and engaged states.

By analysing taxi trajectory data, the algorithm identifies areas where passenger demand for street hailing consistently exceeded the taxi supply, indicating unmet demand. This approach offers a dynamic understanding of demand patterns compared to traditional methods that relies on historical completed street-hailing rides. The algorithm's ability to provide insights into unmet demand demonstrates the potential data-driven approaches to address the complex challenge of matching taxi supply with street-hailing demand. The insights are particularly valuable for our study to identify approximate potential unserved demand for taxi street-hailing in Jakarta to measure the business impact, enabling us to make informed considerations for proposing the implementation of taxi street hailing detection using computer vision technology.

III. RESEARCH METHODS

In this study, we apply a mixed-method approach combining quantitative and qualitative methods. The combination of these methods is selected to leverage the strengths of each method to provide a more comprehensive and nuanced understanding of the research [15]. The quantitative analysis allows for objective evaluation to the research hypothesis by empirically identifying and analysing patterns within an aggregated secondary data collected from the taxi company for measuring any potential additional taxi street hailing demand that could be served by such traditional taxi company in the future, by implementing the AI and CV technology for street hailing detection. Meanwhile, the qualitative method interprets the collected qualitative data to validate the measurement results from the quantitative method and provides a deeper insights and a richer understanding in a more contextual for interpreting behaviors and preferences accurately [16, 17].

The chosen methodology in Figure 4 is designed to provide comprehensive insights into not only to assess the business impact to find the demand gap that potentially could be absorbed by the taxi company from the AI-based street-hailing detection technology implementation, but also to get understanding on how the technology is integrated effectively as a system.

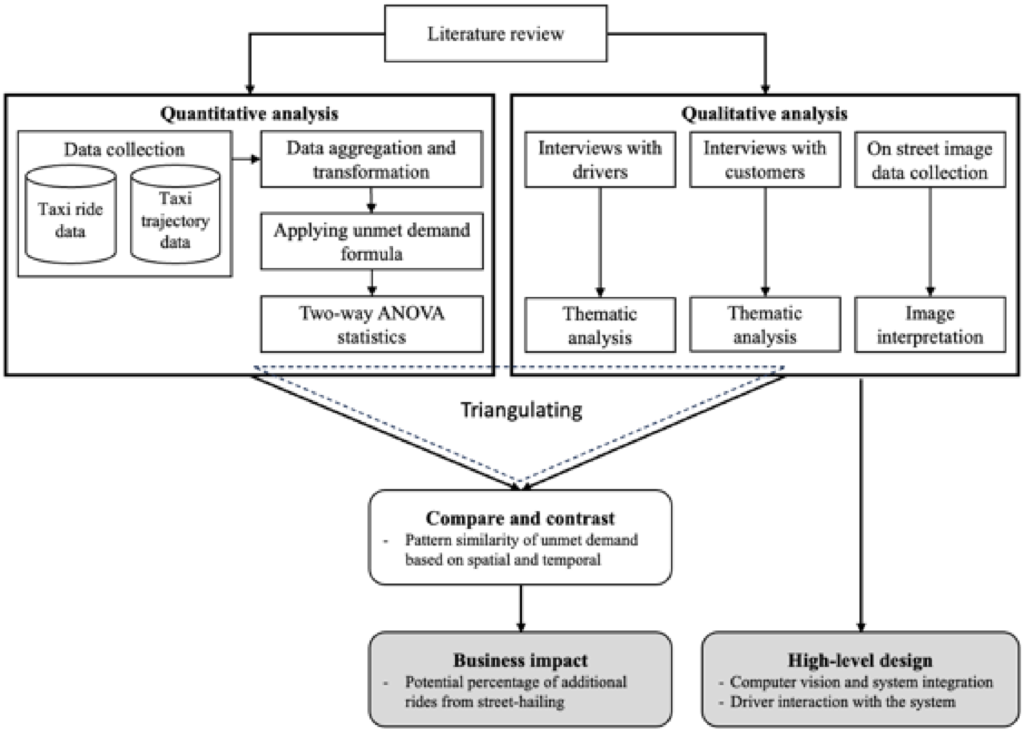

Figure 4. Research design flow.

To figure out the potential of additional rides that can be acquired from unserved demand for taxi street hailing in Jakarta, we conduct a two-month examination of taxi trajectory data within the capital city of Indonesia. By performing both spatial and temporal analysis, we learn the patterns of taxi movements and identify when and where unserved hailing attempts occurs most frequently. We look for patterns that emerge across various city clusters represented with a grid mesh laid over a map of the city

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[14, 18, 19]. The clusters are analyzed temporally on weekdays, weekends, throughout different periods, from morning to night. By segmenting the city into a grid system, a method that is particularly effective for a city near the equator like Jakarta, we can more accurately understand the dynamics of supply and demand for taxi services within different areas in Jakarta. The analysis is complemented by thematic analysis from the interviews with both drivers and customers. The merged insights allow us to strengthen the quantitative findings and validate the estimation of potential unmet demand, revealing patterns across city clusters.

In addition to assessing the business impact, we also explore the conceptual implementation design that could be proposed. The high-level design is suggested to ensure that the system being proposed takes into account the users' expectations, experiences, and needs, making it more likely to be accepted and used effectively. The design also outlines key components and interactions within the system, allowing for early identification of potential technical or practical challenges.

A. Data Collection Method

1) Taxi Trajectory and Taxi Trip Data Collection

The taxi trajectory dataset for this research is a secondary data collected from a taxi company in Indonesia and is used as a basis for quantitative analysis. The data contains records of taxi movements every single minute represented with geospatial information which are sourced from GPS devices installed within each of the taxi company's fleets. The data provides comprehensive insights into the movement along with the operational status of the taxis, at any given point tracking whether they are vacant, enroute to pick up a passenger for an order, or each of them are already with a passenger on board which means unavailable for another passenger at the same time. With such data, we are able to know how long each taxi moves in a certain area in a vacant or occupied state.

Taxi ride data is also utilized to serve as the foundation for the analysis. This secondary data is collected from the recorded successful street hailing taxi rides. The data is collected when each taxi starts the trip. The original dataset includes rides from various sources, but for research purposes, it has been filtered to include only the rides from street-hailing. This filtering process ensures that the data represents instances when and in which particular location passengers hailed taxis directly from the street, excluding any rides booked through app or other platforms.

To enhance the analysis, it is also valuable to consider other temporal information to examine whether it was raining or not on the dates of the trajectory time, or if the dates coincide with a public holiday. The data is then merged with the taxi rides and trajectory data. Aligning the datasets based on their respective timestamps. This additional perspective can provide a comprehensive analysis of how public holidays may influence order patterns and overall demand.

2) Interviews with Customers

To explore how the taxi customers perceive and engage in street-hailing situations and to validate the numerical analysis result from the inferring unmet demand of taxi street hailing, interviews are conducted with the taxi customers especially the street hailers as a primary data collection method. The use of this data aims to identify and analyze the key factors influencing customer preferences, the experiences, and the decision-making processes during street hailing interactions [5].

We interviewed 13 participants who frequently use taxi services (See Table 1). The interviews are designated to ensure a comprehensive understanding of various customer experiences and expectations. A semi-structured interview guide was developed to encourage participants to express their thoughts and experiences freely to get a deeper exploration of the topic, providing valuable qualitative data. The interviews collect information from an open-ended question designed to obtain detailed responses from the informants, such as:

- The customers' preferences for getting a taxi ride and the reason behind it.
- The customer experience when attempting to hail for a taxi on a sidewalk.
- The ethical issues impacted from the implementation of AI and computer vision via taxi dash-cams.

Table 1. Customer respondent profiles.

No.	Initial name	Profession	Age (years)	Gender	Interview Date	Interview Time
1	AR	Security	21 – 30	Male	28 Oct 2024	10:18
2	DA	IT Consultant	31 – 40	Female	27 Jan 2024	06:06
3	IA	Accountant	41 – 50	Female	26 Jan 2024	21:14

4	AF	English Teacher	41 – 50	Female	27 Jan 2024	07:14
5	FR	NGO	41 – 50	Female	28 Jan 2024	10:00
6	FS	Accountant	41 – 50	Female	27 Jan 2024	08:31
7	BF	IT Sales	41 – 50	Female	13 May 2024	20:00
8	MU	IT Engineer	21 – 30	Male	13 May 2024	20:45
9	SF	Content Specialist	21 – 30	Female	12 Apr 2024	15:18
10	PS	Accountant	41 – 50	Female	12 Apr 2024	18:37
11	IR	AI Specialist	31 – 40	Female	3 Jun 2024	13:00
12	PR	Digital Product Manager	21 – 30	Male	3 Jun 2024	13:37
13	DR	Banker	31 – 40	Female	26 May 2024	18:27

3) Interviews with Drivers

The interviews with taxi drivers are conducted to assure that the numerical result coming out from the inferring unmet demand model calculation aligns with the qualitative information obtained from them, such as the time when they usually find the street hailers are not picked up or the location where it mostly happens during their operations. The interviews are also to get insights regarding the experience of the drivers when dealing with the street hailing rides from their perspectives, such as in what condition they may miss the opportunity for picking up customers. This is also to get the understanding of the potential impact from the implementation of AI-based street hailing detection technology, so we can propose the high-level design on how it can be developed in the future. A total of 15 drivers are recruited to join the interview sessions, with distinct of years of experience from 1 year up to 22 years with detail profiles as described in Table 2. Most of the drivers are randomly selected, and the same as the interview sessions with customers, the interviews with the drivers also collect information from open-ended questions to get a more detailed information from them, that can elaborate the main questions of:

- Whether street-hailing is still preferable by drivers.
- Where and when the drivers usually get passengers from street instead of app.
- Challenges faced by the drivers when having a street hailing ride.
- Drivers' opinion regarding the implementation of CV for street hailing detection, and how this implementation will help them to increase their earnings.

Table 2. Driver respondent profiles.

No.	Initial Name	Taxi Driving Experience	Interview Date	Interview Time
1	CN	3 years	18-Apr-2024	17.27
2	YK	8 years	19-Apr-2024	07.10
3	SM	19 years	24-Apr-2024	07.09
4	DS	12 years	11-May-2024	08.34
5	RW	1 years	13-May-2024	07.22
6	KO	11 years	13-May-2024	18.20
7	DM	1 year	13-May-2024	20.34
8	SR	22 years	15-May-2024	07.19
9	ZS	3 years	19-May-2024	11.57
10	AS	2 years	21-May-2024	07.17
11	OG	3 years	27-May-2024	07.10
12	AS	3 years	27-May-2024	18.58
13	SH	1 year	28 May 2024	19:36
14	YT	15 years	29 May 2024	20:00
15	RR	1 year	6 June 2024	18:37

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4) On-Street Image Data Collection

The on-street image data is collected to serve a critical purpose in strengthening our research on taxi hailing patterns. Essentially, this visual information adds a layer of confirmation to the conclusions drawn from our quantitative analysis. By studying imagery of real-life taxi hailing, we can see the behaviors and circumstances surrounding customer attempts to flag down taxis. This help us ensure that our statistical insights are reflective of what's actually happening on the ground. Beyond validation, the imagery also offers us a way to dive deeper into the human elements of street hailing, such as peak times, popular locations, and customer demographics, which are not always apparent in raw data. These findings contribute to a richer, revealing trends and habits that might otherwise remain hidden.

B. Data Analysis Method

1) Inferring Unmet Demand

Following the methodology suggested by Afian et al. (2015), we conduct a quantitative analysis for inferring potential unmet demand in the taxi street-hailing. From the taxi trajectory data, we retrieve the vacant state of the vehicles in Jakarta during February to March 2024 to be aggregated for the calculation of the taxi slack time value in a location cluster in a period of time. The data is clustered spatially and temporally for each vehicle. The spatial data is clustered by creating a grid mesh superimposed on Jakarta map at a zoom level of approximately 1 km x 1 km area. The grid clustering is developed by rounding the geographical coordinates of the taxi trajectory to the nearest hundredth—both latitude and longitude [14]. By rounding the latitude and longitude values to two decimal places, we can group vacant taxis that are in close proximity to each other, effectively aggregating their movements into cluster of location around 1x1 km grid. By temporal, the trajectory time is aggregated every 1 hour. In every hour, we measure how many minutes every taxi is in vacant state. Figure 6 describes how the data is aggregated.

To get the probability of unmet passenger demand for a taxi on a sidewalk, we must look at more than just the taxi slack time. As suggested by Afian et al. (2015), to formulate the problem, we also need to observe number of finished taxi rides through hailing on the street. The same as the taxi slack time data, this actual data of the completed rides is aggregated into hourly intervals and sorted into spatial clusters representing grids of about one square kilo meter each. To gain a comprehensive understanding of unserved demand patterns, the data is segmented into weekdays and weekends/holidays. This segmentation acknowledges the differences in travel behavior and demand patterns between regular working days and days of leisure or non-work, including public holidays.

To assess the impact of weather conditions on unserved demand, the data is further divided into days with and without rain. This segmentation aims to quantify the potential surge in unmet demand during adverse weather, as individuals might be more inclined to utilize street-hailing services when faced with rain. The heavy rain may cause the road traffic to worsen, leading to longer wait times for customers who order a taxi via an app.

Time: 1 Feb 2024, 14:00 - 14:59
Location: (-6.2, 106.78)

Minutes

Taxi ID	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37	38	39	40	41	42	43	44	45	46	47	48	49	50	51	52	53	54	55	56	57	58	59
T1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
T2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
T3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
T4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
T5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0
T6	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
T7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
T8	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1
T9	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
T10	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
T11	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
T12	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
T13	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	0
T14	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0
T15	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
T16	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
T17	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
T18	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	0	0	0
T19	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
T20	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
T21	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
T22	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Free time:																																																												192
Free time per taxi:																																																												8.73

Figure 6. Sample of trajectory of vacant taxis in every minute in one hour within a location grid.

We conduct two-way Analysis of Variance (ANOVA) for the inferential statistics. The two-way ANOVA is conducted as part of the quantitative analysis to reveal insights in the dataset. The two-way ANOVA is chosen as it allows for the simultaneous examination of the effects of two categorical independent variables on a continuous dependent variable, while also assessing potential interaction effects [22–24]. The independent variable for this statistical analysis is percent of unmet demand, a variable derived from the division of potential unmet demand by the total demand. Potential unmet demand is a variable derived from the division of finished orders by the average of taxi free minute, while the total demand is the sum of unmet demand and finished street-hailing rides. The analysis incorporates temporal, spatial, and weather factors.

2) Thematic Analysis from Interviews with Drivers

Given the flexibility benefits of thematic analysis [25], we aim to gain insights from the interviews with drivers as the subject who often interact with street-hailing passengers. The insights are regarding various aspects of street hailing situation perceived by them. This analysis focuses on seven key attributes:

a. *Ride channel preference:* Understanding the preferred ride channel is critical to ensure the street-hailing detection technology is relevant and effective to be implemented.
b. *Most frequent time getting street-hailing:* Understanding when the most frequent time the drivers getting hailed from street. This is to validate the quantitative analysis for inferring unmet demand based on the time.
c. *Most frequent day getting street-hailing:* The same as the most frequent time, but distinct weekends and weekdays.
d. *Most frequent location getting street-hailing:* Understanding in which specific location drivers usually get hailed from street. This is also to validate the quantitative analysis for inferring unmet demand, specific for spatial analysis.
e. *Action when failed to pick-up the street-hailer:* Understanding what usually the drivers do when they are unable to pick-up passengers who hail from street, whether they inform the other drivers nearby or just do nothing.
f. *Reasons of failed to pick up the street-hailer:* Understanding why the drivers are failed to pick-up passengers who attempt to stop taxi on the street. This information is beneficial for identifying parameters for the success of street-hailing detection system.
g. *The usefulness of street-hailing detection system:* Understanding if the technology implementation will be useful or helpful for the drivers.

3) Thematic Analysis from Interviews with Customers

The thematic analysis from the interviews with customers focuses on six key attributes:

a. *Hailing method:* Understanding customers preferred method for hailing a taxi.
b. *Typical street-hailing time:* Understanding when customers typically hail taxis from the street, identifying peak demand periods and potential service gaps.
c. *Typical street-hailing location:* Understanding where customers typically hail taxis, identifying peak demand location and potential service gaps.
d. *Typical waiting time for on street:* Understanding typical customer waiting time on street until getting a taxi.
e. Reason of failed street-hailing attempt: Delving into the reasons why customers fails in hailing a taxi from street.
f. *Acceptable time to wait:* To determine customer's tolerance for waiting when attempting to hail a taxi on the street.
g. *Ethical considerations of the technology implementation:* Exploring customers' perspective on the ethical implications of implementing street-hailing detection system.

4) Image Interpretation

To complement the quantitative and thematic analysis derived from interviews with drivers and customers, visual interpretation of content captured from a YouTube channel offers a unique valuable visual perspective. The visual interpretation approach enriches the existing methodologies by bringing another dimension [26], uncovering insights that may not readily apparent through interviews or numerical analysis. Below is the purpose of the analysis:

a. To identify locations where the customers usually hail a taxi from street.
b. To validate if the taxi supply is one of the issue that the customers is failed to get a taxi when hailing on the street.
c. To validate the time when the passengers mostly hail from the street.
d. To understand the passenger behaviour when hailing in order to get insights for the high-level implementation design of street-hailing detection system.

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IV. RESULTS AND DISCUSSION

A. *ANOVA for Inferential Statistics*

Prior to summarizing our overall findings, we conducted a two-way ANOVA to stringently test our hypotheses. The primary objective of the two-way ANOVA statistics is to evaluate the impact of working days, rain condition, locations, and time in hour on the percent of unmet demand. This statistical approach allowed us to assess both the independent effects of each factor and the potential interaction in relation to the potential unmet demand percentage. This method is later to be complimented with a qualitative validation process. By triangulating the ANOVA statistics with the qualitative insights, we aimed to achieve a more robust understanding of the factors influencing the unmet demand, strengthening the validity and credibility [27] of the potential unmet demand estimation model.

A two-way ANOVA to test the interaction effect between working/non-working days and hour groups on unmet demand percentage, as seen in the interaction plot in Figure 7, indicates that both variables working/non-working days and working hours significantly affect the percent of unmet demand, and there is a significant interaction between these two factors, ($F(1, 8846) = 9.974$, $p < 0.05$) for the variable of working/non-working days and ($F(3, 8846) = 43.260$, $p < 0.05$) for the variable of hours.

The testing result on the interaction effect between working days and hours ($F(3, 8846) = 8.214$, $p < 0.05$) rejects the null hypothesis (see Table 3), suggesting that the impact of working days on percent of unmet demand is dependent on the hours in a day. These findings consistently demonstrate the interactive influence of these variables on the dependent measure, reinforcing the conclusion that both sets of factors significantly impact unmet demand percentage. The interaction plot shows that this effect is most pronounced during the 12:00 – 17:59, where the difference in unmet demand between working days and non-working days is larger compared to other hour groups.

The projected number from the inferring unmet demand reveals a distinct temporal pattern within the days, with working days during working hours or after office hours are potentially giving more significant percentage of unserved street hailing demand compared to non-working days. As can be seen in Figure 7, the percentage of potential unmet demand on working days during working hours is higher than the other combinations of factors, coinciding with the working hours. After working hours, the percent of potential unmet demand even keeps high. It implies that significant portion of customers are unable to hail for taxi services at those specific times. This analysis suggests that the potential unserved demand for hailing on the street is significantly influenced by the commuting patterns and behaviors associated with office worker activity [19].

Table 3. Two-way ANOVA table for the effect of working_day and hour_group of time on unmet demand percentage.

	Sum of squares	df	F	P-value
C(working_day)	0.071	1	9.974	0.002
C(hour_group)	0.929	3	43.260	9.60e-28
C(working_day):C(hour_group)	0.176	3	8.214	1.86e-05
Residual	63.307	8846		

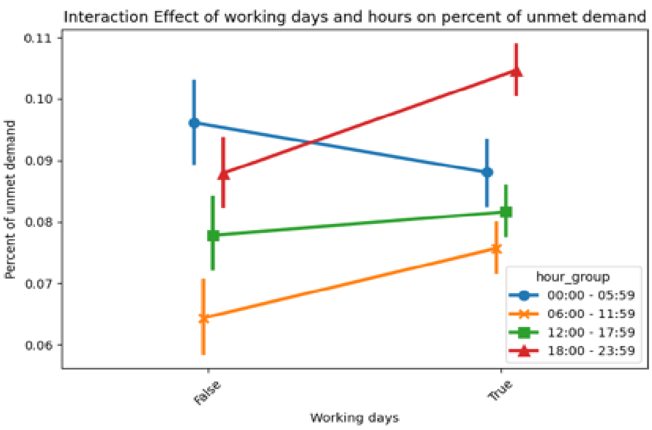

Figure 7. Interaction effect of working_day and hour_group on percent of unmet demand, confidence interval 0.95

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Different results are obtained from another ANOVA testing effects of working days and rainy days on the unmet demand percentage. Even though this second testing indicates that both variables `working_day` and `rainy_day` significantly affect the percent of unmet demand, but there is no significant interaction between these two factors. The testing failed to reject the null hypothesis for the interaction effect between `working_day` and `rainy_day` variables. The main effect of `working_day` ($F(1, 8850) = 5.745$, $p < 0.05$) indicates that unmet demand differs significantly between working days and non-working days (weekends/holidays). Similarly, the main effect of `rainy_day` ($F(1, 8850) = 38.973$, $p < 0.05$) shows a significant difference in percent of unmet demand between rainy and non-rainy days. However the interaction effect between `working_day` and `rainy_day` ($F(1, 8850) = 0.314$, $p >= 0.05$), as can be seen in Table 4, suggests that the impact of working days on percent of unmet demand is not dependent on whether it is a rainy day or not.

Table 4. Two-way ANOVA table for the effect of working_day and rainy_day on unmet demand percentage.

	Sum of squares	df	F	P-value
C(working_day)	0.042	1	5.745	0.017
C(rainy_day)	0.282	1	38.973	4.49e-10
C(working_day):C(rainy_day)	0.002	1	0.314	0.575
Residual	64.128	8850		

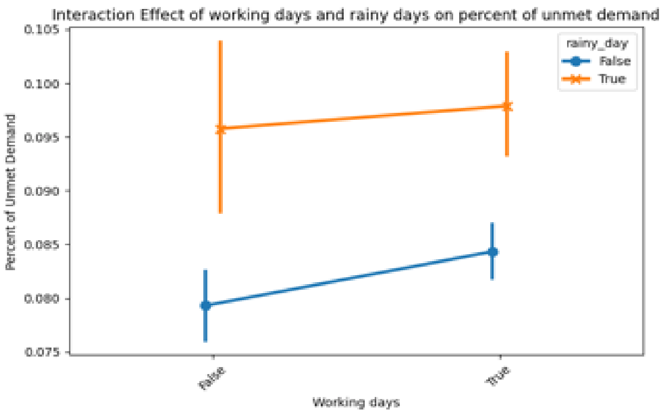

Figure 8. Interaction effect of working_day and rainy_day on percent of unmet demand, with confidence interval of 0.95.

These results highlight the significant influence of both factors except their interaction on unmet demand percentages. Even though the non-parallel line in Figure 8 indicate a potential interaction effect, but on non-working days, the difference in unmet demand percentage between rainy and non-rainy days is small.

The two-way ANOVA testing also examines the effects of locations and working days on the percent of unmet demand. There is a statistically significant difference in the percentage of unmet demand between locations in 5 km x 5 km grids ($p < 0.05$). This implies that different locations significantly impact the unmet demand. The interaction plot in Figure 9 visually displays the results, showing distinct patterns for different combinations of area and working day status. The analysis also reveals a significant interaction between working days and locations (p-value= 0.001818) (see Table 5). This means the effect of locations on the percent of unmet demand depends on the locations.

Table 5. Two-way ANOVA table for the effect of working days and locations on unmet demand percentage.

	Sum of squares	df	F	P-value
C(working_day)	36.623	36	283.278	0
C(locid_5km)	0.070	1	19.511	1.01e-05
C(working_day):C(locid_5km)	0.236	36	1.828	0.001818
Residual	31.534	8781		

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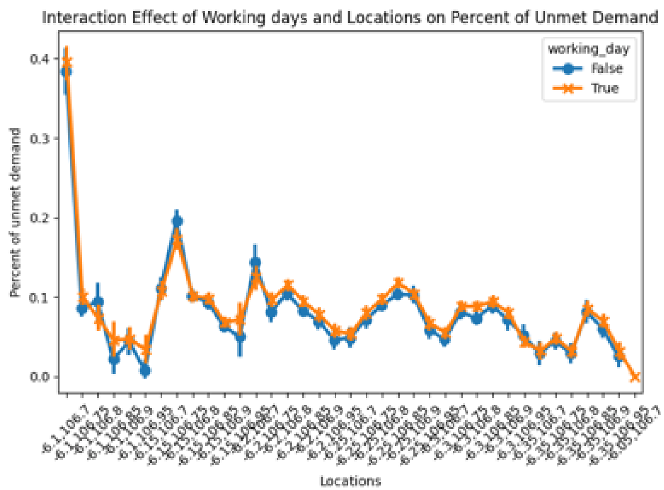

Figure 9. Interaction effect of location grids and working_day on percent of unmet demand, confidence interval 0.95.

In Table 6, a two-way ANOVA results to test the interaction effect between rainy days and hour groups indicate a significant interaction effect between both factors (p = 0.002725). This means that the effect of rainy days on the percentage of unmet demand is not consistent across all hour groups, and vice versa. The effect of one factor depends on the level of the other factor. Looking at the interaction plot in Figure 10, it can be seen clearly that the impact of rainy days on unmet demand is not uniform throughout the hour groups. The effect is most substantial during the 06:00-11:59 hour group, indicating that this period might require special attention in terms of resource allocation during rainy days. Even though not as pronounced as the 06:00-11:59 hour group, the 12:00-17:59 and 18:00-23:59 hour groups is noticeable, with slightly higher unmet demand on rainy days.

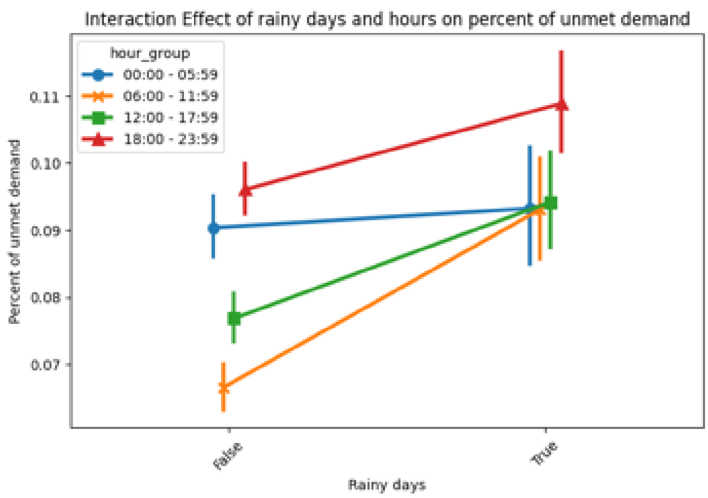

Figure 10. Interaction effect of locations grids and working days on percent of unmet demand, confidence interval 0.95.

Table 6. Two-way ANOVA table for the effect of rainy days and locations on unmet demand percentage.

	Sum of squares	df	F	P-value
C(rainy_day)	0.309	1	43.280	5.01e-11
C(hour_group)	0.926	3	43.221	1.02e-27
C(rainy_day):C(hour_group)	0.101	3	4.716	0.002725
Residual	63.145	8846		

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When testing the interaction between factors of locations (locid_5km) and rainy conditions (rainy_day), unlike the previous result in Table 6, that the p-value shows that the rainy_day factor has a significant effect to the percent unmet demand, when testing the interaction with factor locations, the rainy day doesn't show the significant effect, which only has p-value 1.0 (see Table 7). This differences in the P-values for `rainy_day` between the two ANOVA tables can be attributed to the distinct models and variables included in each analysis. In Table 7, which includes locid_5km as a categorical variable and its interaction with `rainy_day`, the sum of squares for `rainy_day` is effectively zero, indicating that when the location is accounted for, the variation due to `rainy_day` is negligible. This suggests that the impact of `rainy_day` is fully explained by the location differences and their interactions, rendering its direct effect insignificant.

Even though there is no significant effect of rainy days (p=1.0), however the two-way ANOVA results show that a significant effect is found ($p<0.05$), implying that the effect of rainy days on percent of unmet demand depends on the specific location. The interaction plot in Figure 11 visualizes this relationship, showing how the impact of rainy days varies across different locations.

A two-way ANOVA statistic to test the interaction between hours and locations has a result that there is a significant interaction effect between location and hour group ($p < 0.05$) (see Table 8). This indicates that the effect of the hour group on unmet demand varies depending on the location. As can be seen in Figure 12, visually confirms the significant effect. The non-parallel lines demonstrate that the effect of hour group on unmet demand is not consistent across all locations. The differences in unmet demand percentage between hour groups are more pronounced in some locations compared to the others. For example, in some locations, the difference between unmet demand in the 00:00 – 05:59 hour group and the 12:00 – 17:59 hour group is large, while in other locations, this difference is minimal.

Table 7. Two-way ANOVA table for the effect of locations grids and rainy days on unmet demand percentage.

	Sum of squares	df	F	P-value
C(locid_5km)	32.649	36	255.901	0
C(rainy_day)	0.000	1	0	1.0
C(locid_5km):C(rainy_day)	0.713	36	5.592	0
Residual	31.120	8781		

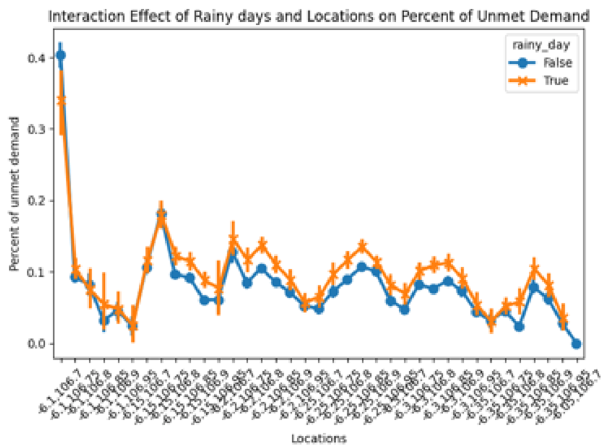

Figure 11. Interaction effect of location grids and rainy days on percent of unmet demand with confidence interval 0.95.

Table 8. Two-way ANOVA table for the effect of locations and groups of hours on unmet demand percentage.

	Sum of squares	df	F	P-value
C(locid_5km)	43.760	36	382.272	0
C(hour_group)	0.556	3	58.321	2.55e-37
C(locid_5km):C(hour_group)	3.591	108	10.456	1.04e-157
Residual	27.693	8709		

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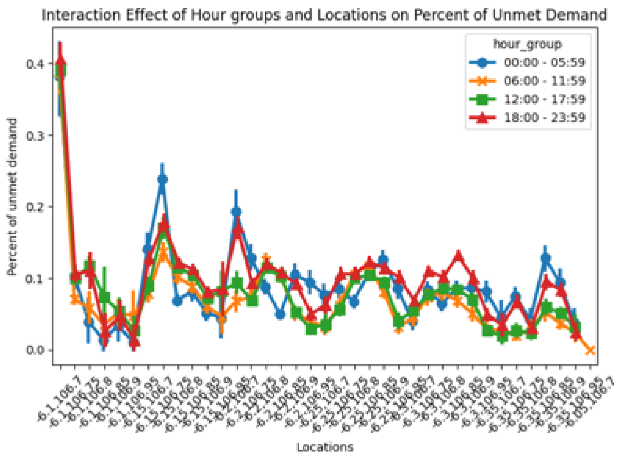

Figure 12. Interaction effect of factors of locations and hours on percent of unmet demand with confidence interval 0.95.

B. Triangulating ANOVA Statistics with Qualitative Insights

To enrich the understanding and ensure comprehensive conclusions, the author delves into a triangulation process by integrating qualitative analysis insights collected from customers and drivers interviews, as well as visual data from captured videos. A thematic analysis is applied, a systematic approach to identify, analyse, and report patterns within the qualitative data. This methodology enables us to get meaningful connections between the statistical results and the qualitative narratives, increasing confidence in the findings through the confirmation from both qualitative and quantitative methods [28].

The patterns from the ANOVA statistics are consistent with feedback from both customers and drivers, confirming the times when demand is usually not fully met. As can be seen in Table 9 column b, driver feedbacks highlighted that the highest frequency of street hailing demand occurs during working hours and extending into the after-office hours, specifically from 8 AM until 7 PM. 14 of them mentioned that the street hailing demand is consistently high, either in the morning from 8 AM to 10 AM, during lunch time between 12 PM and 2 PM, or after-office hours from 4 PM to 7 PM. In addition of it, in Table 9 column c, the thematic result confirms that all the drivers that were interviewed consistently mentioned that the street-hailing demand is high during working days. The drivers observe a consistent stream of taxi street-hailing demand throughout these days as people commute to and from work. A respondent, a driver with initial ZS mentioned during the interview the time when many demand are not successfully served.

Driver ZS: *"During lunch time. I prefer to get passenger from the street, usually to the office area like Mega Kuningan, Sudirman, SCBD. In the morning, the street hailing is usually at the train station exit, many people got off the train, and some of them wait for taxis afterwards. Usually (the destination is) to the office area."* (source: author)

The thematic result from the interviews with customers also says similar pattern. From 13 customers that were interviewed, 9 of them mentioned that the typical street-hailing demand is at noon, the time when they go for lunch (see Table 10 column b). Eight of them mentioned that they also demand for street-hailing after office hours, and 4 of them mentioned morning as the typical time for street hailing. They usually hail for a taxi in the morning to travel from train station to their office. This strengthen the insight that the street-hailing demand is high when people commute to and from work and go for lunch during their working times. They typically wait for a taxi on the street ranging from 1 until 15 minutes, and sometimes they fail attempting the hailing.

From the customer feedback, the majority (9 out of 13) of customers reported waiting for a taxi over 5 minutes on the street, with 3 out of 13 experiencing wait times exceeding 10 minutes (see Table 10 column d). Many of them reported that they use taxi mostly for their daily activity during working days. As seen in Table 10 column c, from 13 customers who were interviewed, 10 of them mentioned that they usually hail a taxi on the street around their office. They stop taxi instead of order from app when they need a taxi immediately to visit their client's offices, go for lunch, or go home from work. The flexibility of hailing a taxi on a street without needing to open the taxi reservation app and waiting the driver to pick them up on the spot is an ideal choice for business professionals who need to hop on and off the taxi quickly. In addition to confirm the numeric analysis, unlike weekdays, none of the drivers or customers reported the high demand for a taxi from street hailing happening on weekends.

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Table 9. Result of thematic analysis from interviews with drivers.

No.	Initial Name	(a) Ride channel preference			(b) Most frequent time getting street-hailing					(c) Most frequent day getting street-hailing		(d) Most frequent location getting street-hailing								(e) Action / how to inform other drivers when failed to pick up hailing customer					(f) Reasons of failed to pick up the street-hailer						(g) The usefulness of street-hailing detection system		
		Street	App	Any	Early morning (3-5 am)	Morning (8-10 am)	Lunch time (12-2 pm)	After office hours (4-7 pm)	Raining	Weekdays	Weekends / public holiday	Sudirman	Kuningan	Thamrin	Senayan	Rawasari	Train/bus station	Shopping mall	Night club	Call command center	Hand signal when pass by others	Text message to chat group	Voice message to chat group	Difficult / Do nothing	On call for order	Avoiding sudden stop / too late	Focus driving	Driving on middle or fast lane	Driving back to taxi pool	Another passenger on-board	Very helpful	Helpful	Don't know
1	CN			✓				✓		✓		✓	✓	✓										✓	✓	✓						✓	
2	YK			✓				✓	✓	✓		✓	✓	✓										✓	✓				✓	✓	✓		
3	SM			✓			✓			✓		✓		✓										✓		✓						✓	
4	DS		✓				✓			✓		✓	✓										✓					✓		✓		✓	
5	RW			✓			✓	✓		✓		✓	✓	✓	✓						✓	✓	✓		✓					✓		✓	
6	KO			✓					✓	✓		✓	✓			✓								✓	✓								✓
7	DM			✓		✓	✓	✓		✓		✓						✓						✓	✓								✓
8	SR	✓						✓		✓		✓					✓			✓	✓				✓			✓		✓		✓	
9	ZS	✓				✓	✓	✓	✓	✓		✓	✓				✓					✓	✓		✓		✓					✓	
10	AS	✓				✓			✓	✓													✓		✓						✓		
11	OG	✓				✓	✓		✓	✓		✓	✓				✓							✓	✓		✓				✓		
12	AS			✓			✓			✓		✓		✓			✓							✓	✓						✓		
13	SH		✓		✓					✓		✓							✓					✓	✓			✓			✓		
14	YT	✓			✓			✓		✓		✓	✓	✓					✓					✓	✓	✓							✓
15	RR	✓					✓	✓	✓	✓			✓				✓					✓			✓	✓		✓				✓	
Total		**6**	**2**	**7**	**2**	**4**	**8**	**8**	**6**	**15**	**0**	**13**	**9**	**6**	**1**	**1**	**5**	**1**	**2**	**1**	**2**	**3**	**4**	**9**	**13**	**4**	**2**	**4**	**1**	**4**	**5**	**7**	**3**

From the interviews with drivers, the customers are not picked-up, most of the case are due to the taxis are already assigned for picking-up the other customers, with 13 drivers mentioned it (see Table 10 column f). The customers who were interviewed mentioned that they mostly fail to attempt the hailing due to either the taxi is already with a passenger, or the driver is driving too fast, in the middle or fast lane. The second reason can be assumed that the drivers are driving fast since they are going to pick up a passenger for an order.

The uncertainty about whether a taxi is vacant or occupied is also often identified by the drivers. Taxis are equipped with a sign above the vehicle that indicates whether the taxi is vacant or occupied. When the light on the sign is illuminated, it signifies that the taxi is available for passengers. Conversely, when the light is off, it indicates that the taxi is currently occupied. However, during daylight hours, the visibility of this sign can be problematic. The brightness of natural light can make it difficult for some

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customers to convince if the sign is on or off. As described in Table 9 column f, 4 of 15 drivers mention that they often found that many customers hailing the taxi in the business districts when it is occupied, and it is often during the lunch time around 12 PM to 2 PM. Customer feedbacks align with the drivers' observation, as can be seen in Table 10 column e, 8 of 13 respondents mentioned that they are usually failed to attempt the hailing from street since the drivers are already with other passengers. They sometimes couldn't distinguish whether the taxi is vacant.

Table 10. Result of thematic analysis from interviews with drivers.

		(a) Hailing method			**(b)** Typical street-hailing time				**(c)** Typical street-hailing location								**(d)** Typical waiting time on street			**(e)** Reason of failed street-hailing attempt				**(f)** Acceptable time to wait				**(g)** Ethical considerations of the technology implementation				
No.	Initial Name	Street-hailing	Mobile app	Call	Noon	After office	Morning	Raining	Kuningan	Senayan	Sudirman	Slipi	Office	Mall	Hospital	Train station exit / bus	1-5 minutes	6-10 minutes	10-15 minutes	With passenger	Driver in the middle / too	Night / low visibility	Seems pickup order	1-5 minutes	6-10 minutes	10-15 minutes	20-30 minutes	Masking face data when	Comply with privacy	Secure the data	Strict used by the	No concern
1	AR	✓					✓		✓								✓			✓	✓						✓					✓
2	DA	✓				✓	✓		✓							✓		✓		✓	✓				✓						✓	
3	IA	✓	✓		✓	✓							✓	✓	✓			✓		✓						✓					✓	
4	AF	✓	✓	✓		✓							✓	✓			✓			✓							✓				✓	
5	FR	✓	✓		✓				✓	✓			✓	✓					✓	✓						✓					✓	
6	FS	✓	✓		✓	✓			✓	✓			✓				✓						✓	✓							✓	
7	BF	✓			✓	✓							✓					✓			✓		✓			✓						✓
8	MU	✓	✓		✓	✓							✓	✓				✓		✓						✓						✓
9	SF	✓	✓		✓		✓				✓		✓			✓		✓							✓						✓	
10	PS	✓	✓			✓													✓	✓							✓				✓	
11	IR	✓	✓		✓						✓		✓	✓					✓		✓	✓	✓			✓		✓	✓	✓		
12	PR	✓	✓		✓								✓	✓			✓				✓					✓						✓
13	DR	✓			✓	✓	✓	✓				✓	✓			✓		✓		✓	✓	✓				✓					✓	
Total		**13**	**9**	**1**	**9**	**8**	**4**	**1**	**4**	**2**	**2**	**1**	**10**	**6**	**1**	**3**	**4**	**6**	**3**	**8**	**6**	**2**	**3**	**1**	**2**	**7**	**3**	**1**	**1**	**1**	**8**	**4**

In rainy days, the already high working-hour demand for street-hailed taxis can amplify the demand even higher. The rainy conditions typically cause discomfort for individuals who might usually walk, use motorcycle taxi, or other mass transit [29]. Especially during working days, due to the necessary for commuting or work-related activities, the rainfall causes the commuters altering the travel modes to taxi [30]. As a result, more people opt for taxis to transport to avoid the inconvenience and discomfort associated with rainy weather. A video recording captured by Driver ZS on his dash-cam provides a compelling visual evidence of the substantial taxi street-hailing demand on a rainy day. While he was assigned to pick up a customer who had made an order, the footage in Figure 13 depicts that at least five other individuals were captured attempting to hail his taxi at the exit of a train station.

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This scene highlights the increment for a taxi and validates the quantitative analysis result regarding the higher unmet taxi street hailing demand during such conditions.

Driver ZS mentioned *"I have a video capturing a moment when they (customers) were attempting to hail my taxi when I drove passed through an LRT station exit near that building (Lenmark building in Sudirman area). It was raining. At that time I already had an order to be picked-up. I waved my hand to signal that I couldn't pick one up."*.

At least one of the interviews with a customer also confirms this rainy condition: *"During the evening after office hour, I often struggle to find an available taxi on the street. They are often occupied. Even worse, when raining."*

The potential unmet demand heatmap analysis is confirmed by most of the drivers who were interviewed that they get passengers who hail on street mostly in those zones. Sudirman area is the most mentioned location that has many street hailing demands, with 11 of 13 drivers mentioned it (see Table 9 column d). Similar to the temporal analysis result of the taxi street hailing demand in Jakarta wide, the demand in this specific business district area also peaks during the morning rush hour around 8-10 PM, lunch break, and after office hour (around 5-7 PM). This observation aligns with findings from previous studies on taxi demand patterns in urban areas, which often correlate with commuting patterns and peak hours for work and leisure activities [2].

Figure 13. Rainy condition, at least 5 customers in less than one minute were attempting to stop a taxi while the driver was on call for another order[20].

From customer perspective, while they didn't explicitly mention Sudirman most frequently, only 2 of 13 customers mentioned it (see Table 10 column c), their frequent references to office areas indirectly highlight Sudirman area as a major business district with a high concentration of office buildings. The customers who were interviewed also confirm the that they usually get a taxi from hailing on the street during working hours, when they go for a lunch or visit their client's offices which are mostly around Jakarta business districts.

C. Potential Unserved Taxi Street Hailing Demand in Jakarta

The merging of results from both the ANOVA statistics, thematic analysis from interviews, and image interpretation has provided a robust foundation for estimating potential demand. Given the consistent patterns observed across both quantitative and qualitative analysis approach, the next step is to delve into the data to refine our demand estimation for street-hailing. This involves constructing histograms and box plots to visualize the distribution of potential unmet demand. Histogram provides a visualization of the frequency of the distribution represented by the areas of rectangles centered on the class interval [31], revealing central tendencies, variability, and potential outliers. This enables the identification of general trends and variability between different groups of categories. Complementing the histograms, box plot or box-and-whisker plot displays important characteristics of the observed data to see the IQR and the outside observations [29]. This visualize the distribution of potential unmet demand percentage so it can be summarized in a number range.

To broaden the analysis, the hourly data in various locations is aggregated into daily summaries. This transformation allows us to examine broader trends and patterns in potential unmet demand. From the implementation of the heuristic algorithm developed by Afian et al. (2015), our research findings indicate that the taxi company most of observed time in daily basis has a potential

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percentage of unmet demand concentrated between 8%-12% (see a histogram in Figure 14). This suggests a quite significant opportunity for the business to gain more revenue by effectively addressing this unmet street hailing demand. Incorporating qualitative insights obtained through interviews with both customers and drivers, and captured image from a dash-cam, this mixed-method approach validates and strengthens the detail findings in that quantitative analysis [32].

As can be seen in Figure 14, the distribution shows a decreasing trend in frequency as the percentage of unmet demand increases, suggesting that while less frequent, there are instances where the unmet demand rises above 12%, reaching up to 16% in some cases. These spikes indicate that on certain days, the potential demand for taxis from street-hailing significantly surpasses the available supply, potentially lead to longer wait times. The presence of a few outliers with potential unmet demand is approximated as high as 15% highlights occasional spikes that needs attention (see Figure 15a). Meanwhile, the absence of bars between 0 and 6% reveals that there is always at some degree of potentially unmet demand, even if it is minimal. This implies that the service is might not always be perfectly efficient in matching supply with demand, leaving a small fraction of potential customers unserved on a daily basis.

The comparative box plots in Figure 15b and Figure 15c reveal distinct differences in the distribution of daily percentage of potential unmet demand between weekends/holidays and weekdays. The box plot for weekdays depicts a potentially higher median with most days potentially experiencing an unmet demand percentage between the 10% and 12% range (see Figure 15b). While the percentage of unmet demand in the weekends/holidays potentially reveals a lower median which typically fluctuates between 8% and 9% (see Figure 15c). Moreover, the narrow IQR indicates the greater consistency in unmet demand during weekends or holidays.

In detail for the weekdays analysis which is higher than the weekends/holidays, the projected number from the inferring unmet demand reveals a distinct temporal pattern within the days, with weekdays are potentially giving more significant percentage of unserved street hailing demand compared to weekends. As can be seen in Figure 16, the potential unserved demand on weekdays ranging from 6% to 18% from 6 AM until midnight, coinciding with the working hours, with the peak can approximately reach 23% at around 6 AM–12 PM. It implies that significant portion of customers are unable to hail for taxi services at those specific times. This analysis suggests that the potential unserved demand for hailing on the street is significantly influenced by the commuting patterns and behaviors associated with office worker activity [19].

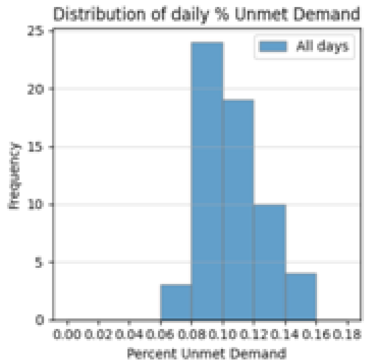
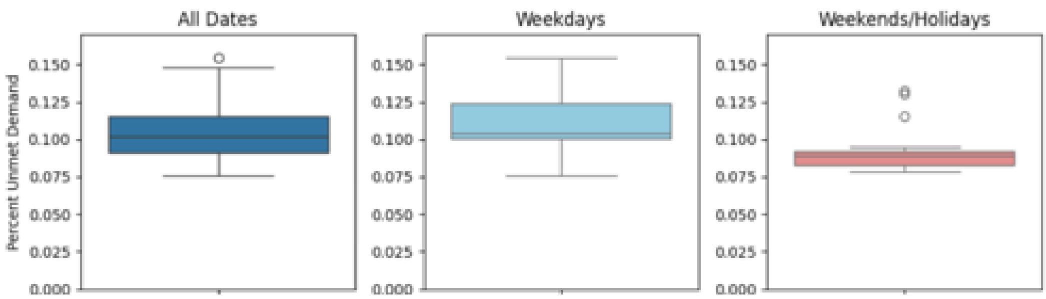


Figure 14. Histogram of daily potential unmet demand percentage.



(a) (b) (c)

Figure 15. Box plot of daily unmet demand percentage in all days (a) and categorized into weekends or holidays only (b), and during working days (c)

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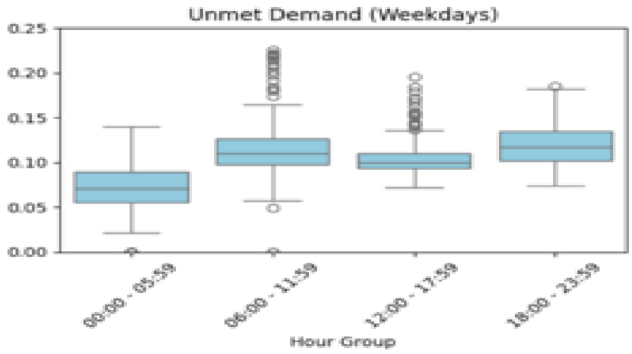

Figure 16. Distribution of percent potential unmet demand to the current actual street hailing rides by hour groups.

D. Business Solution and System Design

To address the unserved demand for a taxi from street hailing, the author proposes a street hailing detection system that utilizes CV technology. The system would be deployed on taxis using cameras attached on the car dashboard facing towards the road ahead and a bit angled towards the sidewalks. The camera would analyze street scenes and identify passengers. The system would be trained on a dataset of images and videos of people hailing taxis, enabling it to recognize specific gestures and actions associated with street hailing.

When a potential passenger is identified, the system would alert the taxi driver, who could then decide whether to stop and pick up the passenger. The minimum distance to detect the hailing passenger should also be considered in the implementation so that the driver could break and safely stop the car directly where the passenger is standing. This is important because at least 4 of 15 drivers who were interviewed mentioned that they are sometimes too late to realize that a customer is hailing and tend to decide to continue driving and ignore the customer in order to avoid a collision due to a sudden break (see Table 9 column f). In addition, in the process of the system when detecting the street hailing, the system would also collect data on street-hailing events, including geospatial data and the time. This data would be used to further refine the system's accuracy and to identify areas and times with high demand for street hailing. This overall scenario is illustrated in Figure 17a.

In Figure 17b, when the driver could not pick up the passenger for any reason, the system would find the nearest taxi around to send alert to that taxi driver. The notified driver then would get a navigation to go to the potential passenger. This could address the current challenge where drivers often fail to communicate potential passengers to their colleagues due to focusing on driving. Our interviews with 15 drivers revealed that nine of them take no action when getting a hailing customer while unable to pick them up, as described in Table 9 column e. Even, for the rest six drivers, at least they don't have to manually inform their colleagues through group message, calling command center, or signaling with hand. While the system finding the nearest vehicle, at the same time the system would record the event as a hailing demand even though no acceptable nearest driver is found. This data would be beneficial for future demand analysis.

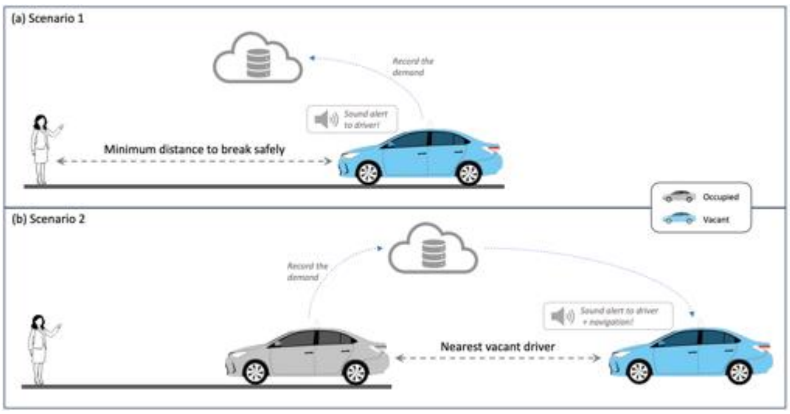

Figure 17. High-level implementation of street hailing detection when a taxi detecting street-hailing is in vacant state (a), and when the taxi is occupied which then send notification to the nearest vacant taxi (b)

To find the nearest taxi, it is suggested from the interviews with customers (see Table 10 column f) that the assigned driver should not be longer than 15 minutes as it is the acceptable time for the customers to wait for a taxi. Longer than the defined limit would cause the customers find another alternative to transport. From the driver perspective, at least one of the participants suggests the implementation should consider the distance from the driver location when receive the notification to the target location of the passenger. It should be less than 500 meters.

By explaining the drivers who were interviewed about the implementation of street hailing detection using CV, describing how it would work, the interviews also asked to know the respondent opinion if the system is implemented in the future. 12 of 15 drivers think that this technology would be helpful for them (see Table 9 column f). Even five of them are really excited to see that system, expecting that they will not miss the opportunity of street hailing demand that sometimes cannot match with the location and time of the taxi supply.

The implementation of street-hailing detection technology raises ethical concerns regarding privacy. As can be seen in Table 10 column g, most of the customers we interviewed highlight the importance of the taxi service adhering to privacy regulations, ensuring data security, and restricting data usage solely to the company. One of them even advocate for real-time data masking before storage. These varying viewpoints highlight the need for balanced approach that prioritizes both innovation and privacy protection in the deployment of the technology.

V. CONCLUSION

Given the observed similarities in patterns between the quantitative and qualitative data we collected, by leveraging the model developed by Afian et al. (2015), we have attempted to infer the potential demand for taxi services in Jakarta that currently remains unmet. Specifically, we estimate that approximately 8% to 12% more street-hailing rides could be accommodated in a common condition. In a special case such as rainy weather in a working day, the additional demand can reach up to 16%. The findings align with qualitative data from the drivers we interviewed who frequently find customers unable to be picked-up, and from the customers who report difficulties finding taxis mostly during rush hour, highlighting the need for improved availability and accessibility. The implementation of CV technology for street-hailing detection could potentially tap into this unmet demand, allowing taxi companies in Jakarta to fulfil an additional 8% to 12% of current street hailing rides. This would require a well-designed system that effectively interprets customer behavior when hailing a taxi on the street. By optimizing the unserved demand, taxi companies could significantly enhance their service efficiency and revenue.

Limitations and Future Research

This study primarily focuses in Jakarta, offering insights specific to its urban transportation dynamics. While our findings are valuable, several limitations should be acknowledged.

1. The quantitative data may not capture all variables influencing taxi demand.
2. The ethical considerations, even though highlighted, require more in-depth analysis, particularly regarding the technical aspects of ensuring privacy and data security in CV systems.
3. While informative, the qualitative data may not be fully representative due to the limited number of interviews.

To build upon this research, future studies could consider the following:

1. Conducting longitudinal studies over multiple seasons and years would allow for the observation of changes in potential unserved demand pattern and the evaluation of the long-term impact.
2. Evaluating the broader economic impact of improved taxi availability on urban mobility and quality of life would contribute to a comprehensive understanding of the benefits of such technology implementation.
3. Cost-benefit analysis of street-hailing detection system, considering the investment required for the technology development, and the benefits including revenue increase and other potential feature developed on top of the systems.

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